On Learning based Parameter Calibration and Ramp Metering of Freeway Traffic Systems

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A THESIS SUBMITTED

FOR THE DEGREE OF DOCTOR OF PHILOSOPHY

DEPARTMENT OF ELECTRICAL AND COMPUTER ENGINEERING

NATIONAL UNIVERSITY OF SINGAPORE

2013

Acknowledgments

I would like to express my deepest appreciation to Prof. Jian-Xin Xu for his generous support, excellent guidance, and encouragement. His erudite academic knowledge, professional research experience and precise insights have always been valuable sources and excellent examples for me. I owe an immense debt of gratitude to him for having given me the consistent and generous help about learning and research. Without his kindest help, this thesis and many others would have been impossible.

Thanks also go to Electrical & Computer Engineering Department in National University of Singapore, for the financial support during my pursuit of a PhD.

I would like to thank Dr. Dipti Srinivasan at National University of Singapore, Dr. Balaji Parasumanna and Dr. Vishal Sharma who provided me kind encouragement and constructive suggestions for my research. I am also grateful to all my friends in Energy Management & Microgrid Laboratory, the National University of Singapore. Their kind assistance and friendship have made my life in Singapore exciting and colorful.

Most importantly, I would thank my family members for their support, understanding, patience and love during the past several years. In particular, I would like to thank my wife, Xiao Zhou, for every wonderful moment that she had spent accompanying and supporting me. This thesis, thereupon, is dedicated to her and our beloved daughter, Ai-Xiao Zhao.

Contents

Nomenclature

Symbol	Meaning or Operation
$\forall$	for all
$\exists$	there exists
$\in$	in the set
∞	infinity
$\hat{\theta}$	the estimate of θ
T	a time interval (second)
k	index of time interval
β	constant feedback gain
o	measured occupancy at the downstream location of the merging area
o^*	desired mainstream occupancy
$\boldsymbol{x}$	vector of traffic states
$r_{\max}$	upper bound of ramp metering flow
$r_{\min}$	lower bound of ramp metering flow
$\rho(k)$	mainstream density in the mainstream merging area at time step k (veh/lane/km)
$\rho_d(k)$	desired density in the mainstream merging area at time step k (veh/lane/km)
$\omega(k)$	number of queueing vehicle on the on-ramp link at time step k (veh)
$v(k)$	mainstream traffic speed at time step k (km/hour)
$r(k)$	flow rate of merging traffic on the on-ramp link (veh/hour)
i	index of particle

Symbol	Meaning or Operation
j	index of generation
V_i^j	velocity of particle i at generation j
η^j	weighting factor at generation j
$\eta_{\max}$	initial inertia weight
$\eta_{\min}$	final inertia weight
c_1, c_2	weighting factor
$rand()$	random number uniformly distributed between 0 and 1
$\boldsymbol{\theta}_i^j$	parameters found by particle i at generation j
$\boldsymbol{\theta}_i^p$	personal best solution with the best fitness found so far for the particle i
$\boldsymbol{\theta}_i^g$	global best solution of particle i found so far among a 3-member neighborhood with best fitness
Gen	maximum generation number
ALINEA	Asservissement LIN*é*aire d'Entr*é*e Autoroutière
DVU	Driver Vehicle Unit
FLC	Fuzzy Logic Control
ILC	Iterative Learning Control
ITS	Intelligent Transportation Systems
LCRM	Local Coordinative Ramp Metering
METANET	A macroscopic freeway traffic flow model
MTS	Macroscopic Traffic Scheduling
NR	Newton Raphson
PARAMICS	PARAllel MICroscopic traffic Simulator
PATH	Partners for Advanced Transportation TecHnology
SA	Stochastic Approximation
SPSA	Simultaneous Perturbation Stochastic Approximation
TTS	Total Time Spent
WTTS	Weighted Total Time Spent

Summary

Freeway traffic engineering is an important area in modern intelligent transportation systems (ITS), where solutions are desperately needed to address the emergent societal and environmental problems caused by freeway traffic congestions. Due to the unavailability of land resources for constructing new freeway infrastructures, to improve the efficiency of existing freeway systems is not only a challenging research topic, but also a requirement to freeway system administrators. Freeway traffic modeling and control are the main topics in freeway traffic engineering. In particular, accurate freeway traffic modeling is the basis for design and analysis of freeway traffic control system, while efficient freeway traffic control is the ultimate objective of researches in freeway traffic systems. In this work, the attention is concentrated on learning based parameter calibration for macroscopic traffic flow modeling and design of learning control strategies for local and coordinated freeway ramp metering.

A hybrid iterative parameter calibration algorithm is first proposed for estimating the parameters of macroscopic freeway traffic models. This algorithm is a hybridization of the multivariate Newton-Raphson method and the simultaneous perturbation algorithm. Convergence of parameters is theoretical guaranteed and well demonstrated through applications with real traffic data and comparison with existing method. In particular, the simultaneous perturbation based gradient estimation scheme improves the parametric convergence in face of local minima. An optimal freeway local ramp metering algorithm is then presented, which uses Fuzzy Logic Control (FLC) and Particle Swarm Optimization (PSO). The FLC based ramp metering algorithm effectively handles the freeway system uncertainties and randomness, and the fuzzy rule parameters are optimized through a microscopic traffic simulation based PSO algorithm. A novel Weighted Total Time Spent (WTTS) based cost function is introduced to measure the efficiency of freeway local ramp metering. By minimizing the WTTS, a balance between freeway mainstream traffic and on-ramp traffic is pursued, which has rarely been discussed. A Simultaneous Perturbation Stochastic Approximation (SPSA) based parameter learning scheme is then proposed to adaptively update the parameters of the FLC based local ramp metering algorithm without disturbing the normal freeway operations.

To address the networked freeway ramp metering problem, an FLC based Local Coordinative Ramp Metering (LCRM) algorithm is proposed. By LCRM, a ramp metering controller generates the local ramp metering signals based on not only its local traffic condition but also the traffic conditions at its neighboring controllers. Such an LCRM algorithm enables cooperation among neighboring ramp metering controllers, which effectively improves the efficiency of the overall traffic control system. Finally, we propose a Macroscopic Traffic Scheduling (MTS) method for networked freeway traffic control. The MTS method divides the considered time period of traffic control into intervals, within which reference mainstream densities are assigned to and tracked by the local ramp metering controllers. Using MTS method, the optimal networked freeway ramp metering problem is treated as an optimization problem. Performances of the LCRM and MTS algorithms are improved using the SPSA based parameter learning algorithm. Algorithmic simplicity, low system costs and improved efficiencies are the main contributions of these two methods.

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Chapter 1

Introduction

1.1 Modeling and Control of Freeway Traffic

While the human society are benefiting from the convenience and comfort provided by modern transportation systems, it is also increasingly confronted with various challenges accompanied. With the expansion of metropolitan areas and the increase of private automotive vehicles, traffic congestion have become a major contributing factor to many emerging societal and environmental issues. For instance, traveling time and fuel consumption are increased under congestion, which consequently result in more air pollution, and road safety is reduced. This situation has become even more pushing due to the unavailability of sufficient land resources for construction of new transportation infrastructures, which is traditionally adopted for solving the traffic congestion problems. Under such circumstances, more efficient management and utilization of existing freeway systems are of substantial importance, which has been realized by policy makes and researchers.

Traffic flow modeling and control are important topics on research of freeway systems. Generally speaking, freeway traffic flow models can be classified into two categories: macroscopic and microscopic models. Macroscopic models focus on modeling freeway traffic flow behaviors at the macroscopic level. The traffic flow behaviors are represented by mathematical equations, which generalize the relationships between aggregated state variables, e.g. average traffic flow, density, and speed. Microscopic models, on the other hand, represent traffic flow behaviors by modeling the behaviors of individual Driver-Vehicle-Unit (DVU), e.g. acceleration-deceleration behaviors, lane-changing behaviors, merging and over-taking behaviors. Both models are useful due to their unique characteristics: macroscopic modeling is computationally more efficient, but microscopic modeling is more detailed and intuitive. It is worthwhile mentioning that parameter calibration is required to guarantee accuracies of these models, because parameters vary and are dependent on several factors, for example, freeway geometries, characteristics of driver behaviors, weather conditions etc. Comparatively speaking, calibration of microscopic models is more challenging and expensive, because there is a huge amount of parameters to be investigated (easily over 50). The task of calibrating microscopic traffic models has mainly been carried out by research institutions or industrial enterprises. Calibration of macroscopic models is relatively less demanding due to the smaller size of parameters and the lower cost involved in obtaining sample traffic data.

Control of freeway traffic flow is the core of freeway traffic engineering, where variable speed limit control and ramp metering are the most commonly used methods. Ramp metering has received much attention from researchers due to its good efficiency in dealing with freeway congestion and improving freeway traffic conditions. Freeway ramp metering can be categorized into local and coordinated control strategies. Local ramp metering strategies regulates the freeway links or networks by implementing controllers at each on-ramp link. These controllers can obtain system information at the vicinities of the on-ramp links, and each controller works independently without communication or interaction with other controllers Coordinated ramp metering strategies, on the other hand, control all on-ramp links of the freeway system in a coordinated manner. There is either a control center that derives instructions to influence the behaviors of local controllers, or inter-controller communications and interactions that enables the local controllers to work collaboratively with each other. Local and coordinated freeway ramp metering strategies also pursue different objectives. Local ramp metering strategies aim at maintaining proper traffic conditions at each on-ramp link locally, but traffic conditions at the macroscopic level is not concerned. Coordinated strategies consider traffic conditions of the whole freeway system, and pursue the optimization of it. From a systematic viewpoint, the coordinated ramp metering strategies are obviously more efficient, because freeway traffic networks are integrated systems of interactive subsystems. For example, maintaining optimal freeway traffic flow at an on-ramp link locally will lead to less or no capacity on the freeway mainstream at downstream locations, and consequently renders the downstream neighboring on-ramp link badly performing or uncontrollable. However, it is still worthwhile investigating various local ramp metering problems, because there are cases that on-ramp links are located far away from each other, and hence the coupling among them can be elegantly dismissed. Additionally, ramp metering at the local level are easier to solve and can be studied at lower cost compared with its counterpart at the network level. The formulation of the problem and the methodologies used for studying local ramp metering problems can provide valuable insight on solving the coordinated ramp metering problems.

In the next section, a review of literature on freeway traffic modeling and ramp metering will be provided.

1.2 Literature Review

This section presents a survey of literature pertinent to studies on modeling and control of freeway traffic flow. Accurate modeling of freeway traffic flow is a prerequisite for various other tasks in freeway traffic management, i.e. traffic simulation, system analysis, and control system design. Since model calibration techniques are crucial to ensure the appropriateness and accuracy of traffic flow models for specific applications, they are of significant importance in freeway traffic engineering. Furthermore, experiments with real freeway systems are hard to achieve in practice due to the prohibitive cost, various safety issues, and the importance to maintain routine freeway operations; therefore, reliable traffic flow models are highly desirable for simulation based research activities. Freeway traffic flow models and various parameter calibration techniques will be reviewed in this section. Various control techniques were studied for ramp metering of local and networked freeway systems, and most of them utilized freeway traffic flow models on design and analysis of control systems. These control techniques, ranging from conventional feedback control to recently developed learning control, and artificial intelligence based intelligent control methods, will also all be covered in the next few sections.

1.2.1 Freeway Traffic Flow Modeling

Macroscopic Freeway Traffic Models

Lighthill and Whitham studied the macroscopic modeling of freeway traffic flow using traffic density as the only state variable, but transient behavior of the model is poor [1]. Payne modified this model based on the fluid dynamics theory, and the modified model is continuous in both space and time [2]. This model was further modified to be discrete in space and time by Payne [3]. Another major and important revision to the macroscopic traffic flow model was proposed by Papageorgiou [4] and Cremer and May [5]. This model has received wide acceptance with numerous applications. The improved model (also widely known as the METANET model) is discrete in space and time, and the relationships between state variables, e.g. mean traffic flow, density, and speed, are expressed in the form of nonlinear mathematical equations. There are other macroscopic freeway traffic flow models, and possible modifications on the METANET model was discussed by Karaaslan et al. [6]. These modifications are complementary to the framework of METANET model.

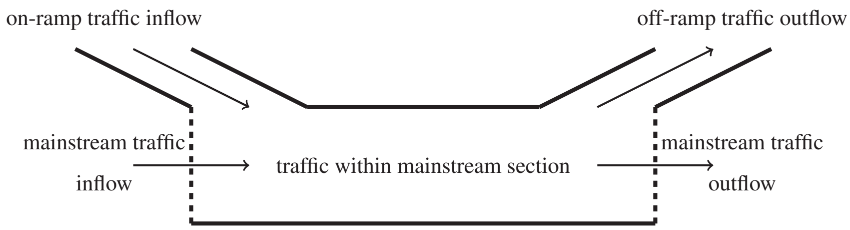


Fig. 1.1: A model of the freeway section with on-ramp and off-ramp links.

In METANET model, a freeway mainstream link is divided into sections. A model of the freeway mainstream section is given in Fig. 1.1. For each mainstream section, on-ramp and off-ramp links might be connected at the beginning and ending locations. Neighboring mainstream sections are correlated by mainstream entering and exiting traffic flows. Empirical elements are incorporated in the METANET model to make it more compatible for practical situations. For example, the empirical fundamental diagram is used, and the impact of exogenous traffic flow to mainstream traffic flow dynamics is also properly modeled. These improvements have made the METANET model especially useful in practical application.

During the evolution of macroscopic freeway traffic flow models, macroscopic traffic flow models has evolved from simple model with single variable to complex models with multiple variables and parameters, from continuous time models to discrete time models, and from purely theoretically derived models to empiricism incorporated models. Due to the improved accuracy, the macroscopic traffic flow models play important roles in many important applications. For instance, model based state estimation of freeway traffic [7–11], prediction of travel time, model based freeway traffic control. However, it has been recently reported that some microscopic traffic flow behaviors, i.e. interactions among vehicles, have substantial influence on macroscopic behaviors of traffic flow [12]. Generalisation of these impacts by extending the METANET model was studied by introducing additional terms in the METANET model [13].

These traffic flow behaviors were also studied from a different perspective of view, which focuses on describing the behaviors of individual Driver Vehicle Unit (DVU) and the interactions among multiple DVU. By such a modeling method, traffic flow behaviors at the microscopic level are investigated. A review of literature on microscopic traffic flow modeling will be provided in the next section.

Microscopic Freeway Traffic Models

Main driver's behaviors described in the microscopic freeway traffic models include acceleration-deceleration behavior, lane-changing behavior, and overtaking behavior, etc. These microscopic behaviors are modeled based on the internal car-following models, on which a summary was provided by Garber [14]. The typical car following and lane-changing behaviors are illustrated in Fig. 1.2. As shown, each vehicle is considered as a DVU, the acceleration and deceleration behaviors of a following DVU is regarded as a response stimulated by behaviors of its leading DVU. This is usually referred as the "stimuli-response" mechanism. The lane-changing and overtaking behaviors involve complex interactions among multiple DVUs, e.g. when a DVU is merging into another lane as shown in Fig. 1.2, it has to pay attention to the status of the DVUs immediately before and after its target position in the new lane as well as vehicles in the front and at the back of its current position. A similar "stimuli-response" based approach is used for modeling of these behaviors.

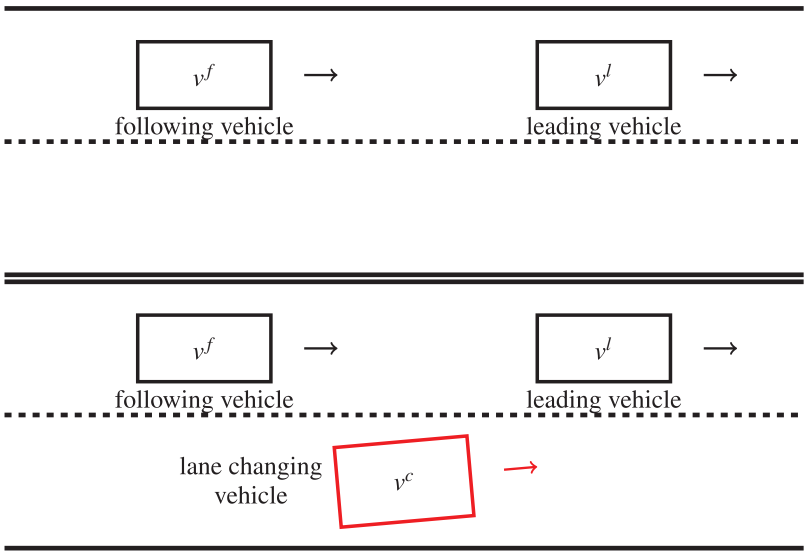


Fig. 1.2: Car following and lane changing behaviors in car following model.

As one of the most popular microscopic traffic simulation platforms, PARAMICS has been widely used for solving various freeway traffic problems [15–18]. In these works, the main reason that microscopic traffic modeling based simulation is favored over macroscopic traffic flow models is that the efficiency of the proposed control algorithms can be evaluated against more realistic traffic conditions.

Although microscopic modelings of freeway traffic can provide detailed and more realistic description of freeway traffic, the number of parameters is usually large (easily over 50), and the model calibration problem become a challenging task. Besides, greater computational power and longer computation time is required when microscopic models are used for freeway traffic simulations. In practice, macroscopic and microscopic traffic flow models can be used according to the specific objective and focal point of the considered problem. If computational cost and simulation time are the main concerns, macroscopic traffic flow models are more suitable options. On the other hand, if the influence of environmental constraints and behaviors of individual vehicles play a substantial role, microscopic traffic flow models serve the objective better.

A detailed summary and comparison on characteristics and important features of various traffic flow models is given in Tab. 1.1.

Category	Macroscopic modeling	Microscopic modeling
Modeling Method	1. Discretized in space and time. 2. Relationships among macroscopic state variables are expressed by mathematical equations.	1. Vehicles are regarded as DVUs. 2. Vehicle behaviors are modelled based on "stimuli-response" effect by car-following models. 3. Road geometry and environments are modeled. 4. Detailed graphical display.
Important Features	1. Computationally efficient. 2. A small number of parameters. 3. Parameter calibration needed.	1. Requires higher computational power. 2. A large number of parameters. 3. Difficult to calibrate.
Examples	1. Payne's model. 2. Lighthill and Whitham model. 3. METANET model.	1. PARAMICS. 2. VISSIM. 3. AIMSUN, etc.

Tab. 1.1: A summary on traffic flow models.

1.2.2 Parameter Calibration

Freeway traffic is a complex process with highly nonlinear traffic flow dynamics, random traffic demand, stochastic driver behaviors and exogenous disturbances. From an engineering perspective of view, macroscopic traffic flow models are always preferred for system analysis and controller design, because macroscopic traffic flow models take the form of mathematical equations and are suitable for efficient programming. Besides, simulations with macroscopic models are more time and cost efficient compared with real experiments. Due to the safety issues, cost issues, and the importance of maintaining normal freeway operations, model based simulations are usually applied to provide theoretical proof on the efficiencies of traffic management measures.

Since parameters of freeway models are varied rather than constant, parameter calibration is essentially required to ensure accuracy and applicability of the model for specific applications. Extended Kalman filtering based algorithms were studied for estimation of freeway traffic states, where parameters of freeway traffic flow model is regarded as part of the freeway states and were estimated together with other freeway traffic states [8–10]. These methods regards parameters of the METANET model as time varying and estimates their values in realtime by the extended kalman filtering algorithm. An iterative learning control (ILC) based parameter identification algorithm was proposed to update parameters of the METANET model by iteratively learning from the discrepancies between the model generated traffic data and measured traffic data [19]. These methods treat the parameters of METANET model as time-varying, and the objective is to track the measured freeway states by output of freeway models through tuning the model parameters.

Parameter calibration problems can also be addressed as optimization problems, where cost functions are defined to measure the discrepancy between model generated traffic data and real traffic data [13]. The parameters that minimizes this discrepancy are pursued. Due to the inherent randomness and disturbances in real freeway system, accurate fitting between model generated traffic data and real traffic data is unachievable. Therefore, traffic flow models can only approximate the traffic flow dynamics using first principle physical laws based mathematical formulae which are able to capture the macroscopic behaviors of the process.

In parameter calibration problems, existing algorithms all adopt a scalar valued cost function. Traffic data can be collected at times or locations, a commonly used method in solving the parameter calibration problem with multiple data sets is to calculate the mean squared error (MSE) with respect to all sample data as the only objective function, and the parameters that lead to the minimum MSE value is considered as optimal. This approach suffers from two main drawbacks. First, the MSE value reflects the averaged fitting accuracy for multiple data sets, while the fitting accuracies for individual data sets are not investigated, e.g. the fitting accuracies might vary greatly among different data sets. Second, accurate convergence of parameters can hardly be guaranteed by existing parameter calibration algorithms. This is because, when scalar valued cost function is used, the system gradient is in the form of gradient vector. It is difficult to ensure the convergence of parameters using existing parameter updating algorithm when highly nonlinear relationship exists between parameters and the cost function. For instance, the Newton-Raphson method [20] requires the inverse of Jacobian, whereas a vector-valued gradient or its pseudo-inverse can not meet the ranking condition.

The heuristic Nelder-Mead algorithm was also studied for parameter calibration of freeway traffic flow model [21–23]. However, this algorithm converges to non-stationary points [24, 25]. Other intelligent algorithms, like PSO and GA, are nature inspired algorithms which have been frequently used for parameter calibration and optimization problems. Yet, they usually require many generations to achieve convergence of parameters, and the local minima problem also limited their application.

Above all, how to achieve convergence of parameters and cope with multiple data sets in parameter calibration requires further studies.

1.2.3 Freeway Traffic Control

Various strategies have been studied for freeway traffic management in the last few decades. Among these strategies, ramp metering has been reported to be efficient in dealing with freeway traffic congestions and improving freeway mainstream traffic flow [26].

A freeway ramp is a section of road which allows vehicles to enter or exit a freeway. An entry ramp is called on-ramp and an exiting ramp is called off-ramp. Ramp metering aims at maintaining proper freeway traffic conditions by regulating the traffic flows entering freeways from the on-ramp entries. Ramp metering is realized by implementation of a device, usually a traffic light or a two-phase (red and green only) signal together with a signal controller at the on-ramp link.

A typical ramp metering system is shown in Fig. 1.3. The freeway mainstream is divided into three main areas around the on-ramp link. The merging area starts from the on-ramp connection point to the end of acceleration lane. The upstream area is the area upstream of the merging area and the downstream area is the area downstream of the merging area.

Existing ramp metering algorithms can be categorized into fixed time strategies and traffic responsive strategies. Fixed time ramp metering strategies adopt fixed ramp metering signals at specific periods of time and have been plagued with low efficiency [27, 28]. Traffic responsive ramp metering strategies determine ramp metering signals according to realtime traffic conditions. Traffic ramp metering strategies can also be

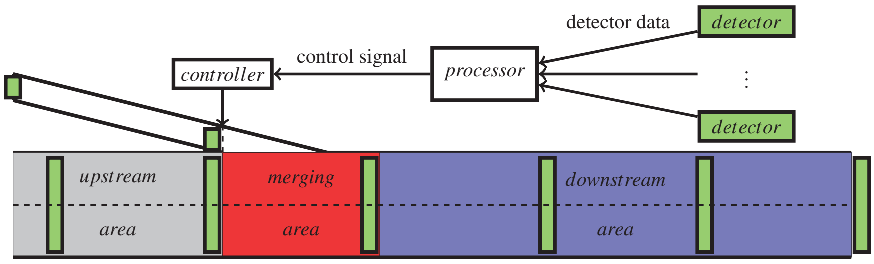


Fig. 1.3: The freeway ramp metering system.

classified into local and coordinated ramp metering strategies based on whether the local traffic measurement or traffic measurement of a wider area is used for determining the local ramp metering signals.

In the following, a review will be provided on various ramp metering strategies..

Fixed-time Ramp Metering strategies

Fixed-time ramp metering strategies are based on constant historical demands, and the ramp metering signals are derived in an off-line fashion for particular times-of-day. Realtime measurements are not used. The traffic flow models are simple static models. Fixed-time ramp metering strategies can be finally regarded as linear programming or quadratic programming problems, which can be solved by readily available computer codes [27].

The main drawback of fixed-time strategies is that ramp metering signals are derived based on historical data, but realtime traffic conditions are not taken into considerations. Efficiencies of the fixed-time strategies may deteriorate because of the variations in traffic demand, which might be caused by freeway system randomness, disturbances and changes in drivers' route choices, unpredictable events etc.

The basis of fixed-time ramp metering strategies is that freeway traffic is a macroscopically repeated process, e.g. roughly repeated traffic demands and congestion hours. By utilizing such a repetitiveness, the system control signals, i.e. ramp metering flow rates, can be properly scheduled so as to obtain the optimal system performance. However, it is quite obvious that freeway traffic demands are not strictly repeated at the microscopic level, on the contrary, they are subject to variations caused by system randomness and disturbances. From this perspective of view, the inefficiencies of fixed-time ramp metering strategies are caused by the utilization of macroscopic freeway traffic repetitiveness for derivation of microscopic control signals.

Note also that although efficiencies of the fixed-time ramp metering strategies are limited, they possess valuable features that are desirable in real implementations, e.g. low implementation cost and simple system structure.

Local Ramp Metering Strategies

Local control strategies determine the ramp metering signals at an on-ramp entry according to traffic conditions at the vicinity of the merging area. The demand-capacity (DC) and occupancy (OCC) strategies determine the ramp flow rate based on the difference between a predefined mainstream flow capacity and the measured mainstream flow upstream of the merging area [29]. The main drawback of these strategies is that a constant mainstream flow capacity is adopted [28]. However, it was reported that mainstream flow capacity may vary substantially due to factors such as weather conditions [30–32].

A number of local ramp metering strategies are based on the fundamental diagram of freeway traffic, which shows the relationship between mainstream traffic flow and density under homogeneous traffic conditions. As shown in Fig. 1.4, mainstream traffic flow achieves the maximum when density is at the critical value, where ρ_c and ρ_{max} are the critical density and maximum density respectively. Since a proportional rela-

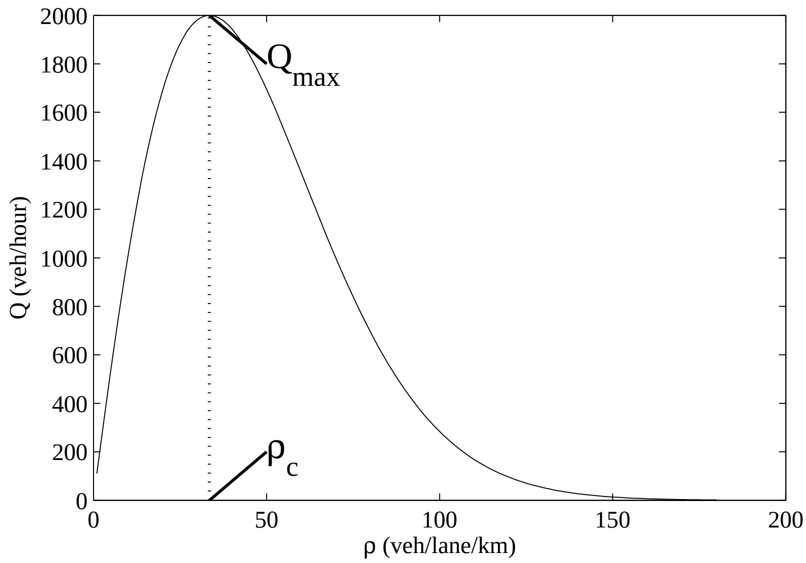


Fig. 1.4: A fundamental diagram of freeway traffic.

tionship exists between freeway occupancy and density, there is a similar fundamental diagram for the relationship between occupancy and flow with a critical occupancy value corresponding the maximum traffic flow.

Some ramp metering strategies aim at maintaining the mainstream density at the critical density by ramp metering so as to maximize the mainstream traffic flow. The feedback based ALINEA algorithm is a well-known ramp metering strategy. By ALINEA, the mainstream occupancy (mainstream traffic density) is measured, and the error between the measured occupancy (density) and the critical occupancy (density) is used to update the ramp metering signal [33]. Adaptive ALINEA algorithms were also proposed, where critical occupancy was considered time varying and estimated in realtime by kalman filtering algorithm [34].

Note that maximum mainstream traffic flow is pursued by most existing ramp metering strategies, e.g. ALINEA and its variants, however, on-ramp traffic conditions are not considered by these strategies except that some queue constraint policies, i.e. put a constraint on the on-ramp queue volume to keep it below a predefined maximum limits [35]. There are two main drawbacks with this strategy: First, the efficiency of the ramp metering strategy at the global level is not investigated, e.g. high queue volume under high traffic demand increases the waiting time spent by vehicles on the on-ramp link although maximum traffic flow is maintained on the mainstream. Second, mainstream traffic capacity (maximum mainstream traffic flow rate) and the critical occupancy and density are varied rather than constant [32], making the maintenance of the maximum mainstream traffic flow a challenging task.

Coordinated Ramp Metering Strategies

Coordinated ramp metering strategies aim at optimizing the performance of the overall freeway network, and the on-ramps within the whole network are controlled in a coordinated manner. To achieve this objective, coordinated ramp metering strategies determine the ramp metering signals according to traffic conditions within the entire freeway network. Total time spent (TTS) by vehicles within the freeway network is usually adopted as the cost function to measure the efficiency of coordinated ramp metering systems.

Coordinated ramp metering algorithm, named HERO, using extended ALINEA algorithm was proposed in [36], where mainstream bottlenecks are identified and local ramp metering controllers work in a coordinated way to avoid traffic congestion and high queue volumes on the on-ramps. The proposed algorithm was reported to outperform uncoordinated local ramp metering and approach the efficiency of sophisticated optimal control schemes. Increased traffic throughput and reduced travel time were also obtained by HERO algorithm.

The Model Predictive Control (MPC) based ramp metering strategies were studied for coordinated ramp metering of freeway networks [28, 37]. Based on historical and predicted freeway demands, the optimal system states, i.e. freeway mainstream densities that minimize the system TTS within N_o time intervals into the future, are calculated. The first N_a (N_a is usually much shorter than N_o) time intervals' solutions are adopted as the reference density signals, which are subsequently tracked by local controllers using ALINEA based algorithm. Combination of the MPC with a game theoretic approach was also studied to seek the optimal ramp metering strategies in [38].

Since MPC based strategies are based on the the frame work of centralized control systems, they suffer from the limitations of centralized control systems also. First, complex model based computation is continuously required to calculate the optimal system states. Second, the centralized organizational structure of the control system lacks flexibility.

It is worth mentioning that, online computation power has been less a problem with the development of computation technologies; however, the problem of organizational structure of MPC remains.

A dual heuristic programming approach was also proposed to solve the coordinated freeway ramp metering problem [39]. This method is based on the frame work of approximate dynamic programming [40], which solves dynamic programming problems by using artificial neural networks based methods. Although, this dual heuristic programming approach provided alternative options in design of control system for networked freeway system, it is still limited to the drawbacks of centralized control.

Above all, further studies are needed to address the drawbacks of centralized control systems.

It is worth noting from the above review that although local ramp metering strategies are less efficient than coordinated ramp metering strategies, they require less implementation cost and have very simple control structures. On the other hand, coordinated ramp metering strategies although can achieved better ramp metering performance compared with local ramp metering strategies, not only require more computation cost, but also increase the system complexity and reduce the system flexibility. Apparently, there is a tradeoff between system efficiency and complexity, flexibility as well as implementation cost.

From the perspective of freeway administrators, it is highly desirable that good system performance can be obtained with low implementation cost but without increasing the system complexity and reducing system flexibility.

There are many other freeway traffic control algorithms studied by researchers in the recent year. In the next session, a review on these techniques will be provided, also reviewed are some key issues regarding studies on freeway traffic.

Actual Implementations of Ramp Metering

Ramp metering as a freeway traffic management measure has been implemented in many areas in the world. One of the most important research program on freeway ramp metering is the $65,000 experiment mandated by the Minnesota State Legislature in 2000. 433 ramp meters were shut off in the Minneapolis-St. Paul area for eight weeks in the study. Results of the study showed that freeway capacity experienced a 9% reduction and freeway speeds dropped by 7% after turning off the ramp meters. Meanwhile travel time increased by 22% and crashes increased by 26%. Due to the persistent controversies on ramp meters, fewer meters are activated during the course of a normal day than prior to this study.

Freeway ramp metering are also studied in California, USA by the Partners for Advanced Transportation TecHnology (PATH), which is under Institute of Transportation Studies (ITS) at the University of California, Berkeley. Studies on freeway traffic modeling, simulation and control has been conducted by the PATH program. In particular, the freeway service patrol project under the PATH program resulted in an set of open access freeway traffic data, which is a useful and valuable resource for studies on freeway research. The freeway traffic data with detailed descriptions of the project and data are available on the internet at `http://ipa.eecs.berkeley.edu/~pettyk/FSP/`. Research experience from research on ramp meters showed that fewer accidents have been achieved.

In Netherland, a coordinated ramp metering system was implemented at the Amsterdam ring road. Results showed that by implementation of the coordinated ramp metering, freeway system efficiency improves and the total time spent by vehicles in the freeway networked is reduced [41]. Similar studies were also conducted in Paris, and similar results were reported [42].

Ramp metering is also implemented in many other countries and areas in the world, e.g. Japan, Australia, New Zealand, Germany, Italy.

Overall, ramp metering is still an alternative option to address the freeway congestion related issues and many studies are devoted to assessing the efficiency of real-time ramp metering system.

Due to the prohibitively high cost of large freeway ramp metering system, the immaturity of large scale optimal ramp metering algorithms and the importance of maintaining normal freeway operation, most of the existing ramp metering programs have been implemented at limited scales.

More future research on optimal control algorithm for large scale freeway systems as well as assessment from real implementations are needed to provide more insight for the policy makers to expand the implementation of ramp metered on existing freeway systems.

1.2.4 Recent Advances and Important Issues

Recent Advances

Artificial Intelligence based algorithms, e.g. fuzzy logic control, genetic algorithm and artificial neural networks, were also investigated for freeway traffic problems. Fuzzy clustering was used for estimation of travel time [43], a type-2 fuzzy logic based approach was proposed for estimation of short term traffic [44], a hybrid fuzzy neural network was proposed for freeway incident detection with linear least square regression [45] and reinforcement learning and multi-agent system based urban traffic control systems were studied [46,47]. FLC based algorithms were reported beneficial to freeway traffic control with good robustness and smoothness of control signal, and improved traffic conditions through microscopic simulation was reported with FLC based ramp metering [48]. Another desirable feature of FLC based control method is that human expert knowledge can be incorporated into the controller design process to improve the control efficiency. This is very important for solving large scale complex systems, where traditional control methods fail but reliable expert knowledge is available.

An FLC based method was proposed for control of networked freeway system where the total time spent (TTS) by vehicles within the freeway system was used as the cost function [49]. A model predictive control (MPC) based methodology was adopted to tune the controller parameters. The MPC based method adopted in the work and several other works [28, 37] is efficient in dealing with various constraints, however, it is also limited in the following aspects. Other applications of FLC for freeway ramp metering can also be found in [50–61].

AI based techniques can be easily implemented due to their heuristic natures and nature inspired concept. However, there are usually a large number of parameters to tuned before they can be really implemented. For example, tuning the input and output membership functions in the FLC algorithms and the connection weights in ANN based algorithms is always a challenging task in dealing with highly complex systems. Besides, most of these algorithms are only suitable for off-line implementations, where the optimal controller settings have to be identified in advance of the implementations.

Traffic Flow Repetitiveness and Randomness

Although randomness exists in freeway systems, e.g. randomness in traffic demands, it is well recognized that the overall freeway traffic is repeated at a macroscopic level. For instance, there are daily morning peak hour traffic from 6 AM to 8 AM and evening peak hour traffic from 5:30 PM to 7:30 PM during weekdays.

Many freeway traffic control methods try to utilize the repetitiveness for various purposes, e.g. fixed-time ramp metering strategies and iterative learning control (ILC) based ramp metering strategies. A common practice in utilization of freeway traffic repetitiveness is to use predefined traffic demand profiles for model based traffic simulations.

ILC is an intelligent learning approach for dealing with reference tracking problems, where the control input signals are iteratively updated based on the output of previous control trial(s). Applications of ILC for freeway ramp metering were studied in [62–66], where predefined reference mainstream densities were tracked by the ILC based ramp metering strategies.

Another way of utilizing the freeway traffic repetitiveness is that the efficiencies of ramp metering algorithms can be evaluated under repeated traffic situations. Hence, historical data can be collected on the controllers' efficiencies with varied parameter settings, which contains information on the impact of parameter variation to the system efficiency. These historical data can be properly exploited to gain insight into the considered system, hence, system performance can be improved by proper adjustment of parameters. Note that the historical data is also contaminated with inherent system noise and disturbances, therefore, it should be properly explored by giving consideration to the adverse effects. Further studies are needed to fully address these issues, especially studies on how to make use of the system repetitiveness with proper handling of the randomness and uncertainties.

Control Objective

The objective of freeway ramp metering has a substantial influence on ramp metering systems, because it measures the efficiencies of various ramp metering strategies.

For coordinated ramp metering problems, TTS has been widely used as the system cost function, and the objective is to find the optimal ramp metering strategies that minimizes the TTS.

For local freeway traffic control, most existing algorithms aim at obtaining optimal mainstream flow through maintaining the mainstream density or occupancy at the critical value. Such a method is limited due to the following considerations:

1. The efficiency of the algorithms depends on estimation of the critical density or occupancy value which is usually defined empirically. In fact it has been revealed that these critical values are time varying and accurate estimation of critical density is still unresolved

2. Freeway traffic under congested traffic conditions is inhomogeneous, but the rela-

tionship between freeway average mainstream flow and density under inhomogeneous is still uninvestigated.

3. The waiting time spent by vehicles on the on-ramp link has not been considered systematically by existing ramp metering algorithms.

Above all, further studies on freeway local ramp metering are needed, which should take the above objective related issues into consideration.

1.3 Focus of the Research and Main Objective

In view of the review in previous sections, main research gaps for the current study of freeway traffic flow theory and control are summarized below:

- Existing parameter calibration methods aim at obtaining parameters with satisfactory performance rather than accurate convergence of parameters towards the optimal parameters. Although gradient based methods theoretically guarantee parametric convergence, they are limited by the local minima problems and complex calculation of system gradient. Research on parameter calibration problems is lacking in providing accurate parametric convergence without involvement of complex model based calculation.

- Existing freeway local ramp metering methods mainly focus on maintaining maximum traffic flow on the freeway mainstream, which makes queueing vehicles be forced to wait on the on-ramp link when traffic load is heavy. Optimal freeway local ramp metering pursuing a balance between mainstream and on-ramp traffic has not been studied.

- FLC combined with effective parameter tuning can approximate any optimal control policies, which is able to improve the system performance without interrupting normal process operation if parameter learning and updating is in a trial to trial fashion. This is essentially a realtime implementable learning control methodology, which has not been studied for freeway ramp metering systems.

- Existing centralized control based coordinated freeway ramp metering systems are limited in high computational cost, complex system structure, and low system flexibility, it is worthwhile to investigate more efficient coordinated ramp metering strategies with simpler system structure, lower computational cost and improved system flexibility. Unfortunately, there has been no such study in literature.

- Existing networked freeway ramp metering strategies with high efficiency requires high implementation cost and have complex system structure, while other methods, which have simpler system structures and require lower implementation costs, are less efficient. It is highly desirable to combine these existing ramp metering strategies into a new networked ramp metering strategy with good system performance, structural simplicity and low implementation cost. This way the advantages of various ramp metering strategies can be fully utilized. However, there has been no such study by now.

Given the above research gaps in modeling and control of freeway traffic flow, the specific objectives of this research were to:

- address the parameter calibration problem of macroscopic traffic flow models by a proposed hybrid iterative algorithm, which provides accurate parametric convergence to the optimal parameters and minimizes the discrepancies between model generated data and real freeway data.

- address the problem of optimal freeway local ramp metering by pursuing a proper balance between traffic on the freeway mainstream link and on-ramp link, and propose a microscopic traffic simulation based parameter tuning approach to find the optimal freeway local ramp metering policies.
- propose a parameter tuning algorithm to adjust parameters of the ramp metering controller, which requires no involvement of complex model based calculation and is suitable for real implementation.
- explore the potential of local coordinative ramp metering strategies for networked freeway ramp metering by combining FLC based coordinative decision making and limited communication among neighboring controllers.
- solve the optimal networked freeway ramp metering problem by a simple but efficient macroscopic traffic scheduling, which combines fixed-time traffic scheduling strategy with a model-free parameter learning scheme to effectively improve the system performance while retaining the simplicity of the fix-time scheduling strategy.

For macroscopic simulations in this research, the METANET model is adopted due to its successful applications in this field. For microscopic simulations, PARAMICS platform (Version 6) is used, which can be viewed as alternative to other similar platforms due to the comparable performances of commonly used microscopic traffic simulation platforms. The parameters of METANET model are treated as time invariant, which is because macroscopic freeway models are expected to generalize the macroscopic level behaviors of freeway traffic flow under various traffic conditions at any time, therefore, a single set of parameters that enable the general applicability of the model for specific freeway system is pursued. Parametric calibration of macroscopic traffic flow models other than METANET is beyond the scope of our research, but could be dealt with in a similarly way as presented here. FLC based algorithms are adopted for both local and coordinated freeway ramp metering, because human expert knowledge can be conveniently incorporated for controller design. Additionally, FLC based algorithms can handle system randomness and uncertainties very well. To adjust the parameters of FLC based ramp metering algorithms and freeway traffic planning, the SPSA based parameter learning algorithm is used due to its superiority in dealing with optimization problems with large dimensional size of parameters. Furthermore, its model-free nature and simplicity make it suitable for realtime implementation.

1.4 Outline of Dissertation

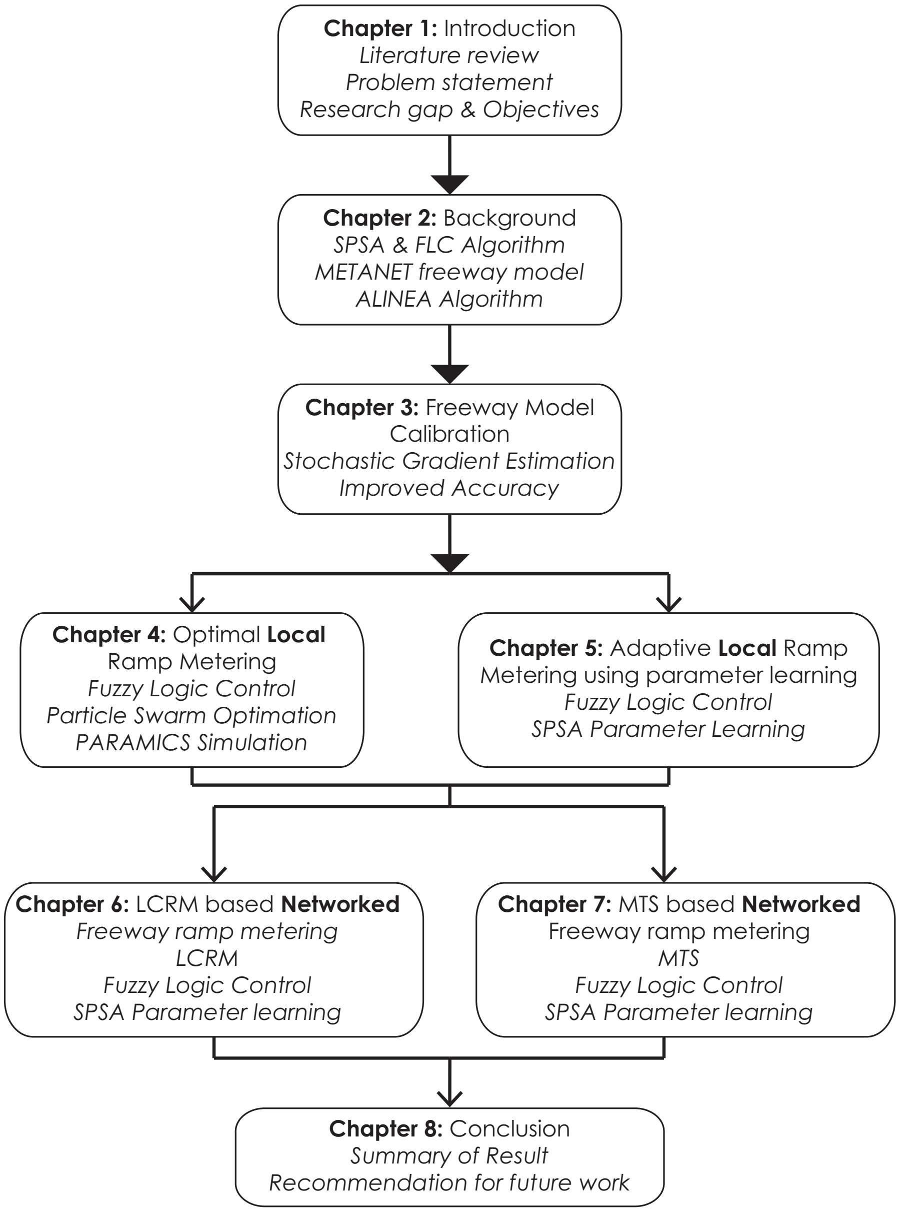


Fig. 1.5: A flow chart on the main content of the thesis.

A flow chart describing the main content of the thesis is shown in Fig. 1.5. As shown, background knowledge and technique information on essential algorithms and the traffic model are provided in Chapters 1 and 2. Chapter 3 is the first technical chapter, where the parameter calibration problem is addressed first. This arrangement of the research topics is because calibrating traffic flow parameters from real traffic data is the first step to conduct model based research on freeway traffic control. Chapters 4 and 5 are on the freeway local ramp metering problem, which is the fundamental topic on freeway traffic control. Chapter 4 focuses on the off-line optimization based method to seek optimal ramp metering policies, while Chapter 5 extends the research to consider the controller parameter optimization problem in an adaptive fashion. The two parameter tuning methods presented in Chapters 4 and 5 can either be used for different traffic systems or used in combination, i.e. off-line optimization is used first to provide reasonable initial point for adaptive learning. The last two chapters discusses the networked freeway ramp metering problem, which extends the works presented in Chapters 4 and 5. Chapter 6 emphasizes the potential of cooperations among neighboring on-ramp metering controllers for improving the overall performance of the freeway system, while Chapter 7 emphasizes the importance of utilizing the macroscopic repetitiveness of freeway traffic. These two networked freeway traffic control methods are suitable for freeway systems with strong interaction among neighboring controllers and strong repetitiveness respectively.

More detailed overview on the content of each chapter are as follows:

Chapter 1 has given an introduction of some relevant background, a brief literature review, the motivation for this research, the objectives and focus of this research, as well as its main contributions.

Chapter 2 provides introductions on the SPSA algorithm, the FLC algorithm and the METANET macroscopic traffic flow model, which are important technical tools and models that the thesis utilizes.

Chapter 3 addresses the problem of parameter calibration for traffic flow modeling using a proposed novel hybrid iterative calibration algorithm. By combining the multivariate Newton-Raphson method with simultaneous perturbation based gradient estimation. The proposed method retains the convergence properties of the multivariate Newton-Raphson method while enhancing the quality of parameter calibration by randomized parameter updating scheme, which help avoid the local minima problem associated with gradient based algorithms. Numerical studies with real traffic data are conducted, demonstrating efficiency of the proposed method.

Chapter 4 investigates the problem of optimal freeway local ramp metering. The objective is set as to achieve a balance between traffic on the freeway mainstream link and on-ramp link. An FLC based local ramp metering algorithm is designed which incorporates human expert knowledge for reducing the fuzzy rule base. Controller parameters are tuned through microscopic simulation based PSO algorithm so to achieve the optimal control performance.

Chapter 5 presents a novel realtime parameter learning based FLC approach for optimal local freeway ramp metering. A simple and efficient SPSA based model-free realtime parameter learning scheme is proposed to tune the parameters of FLC ramp metering controller. System performance is improved by the proposed method without interrupting normal freeway operations.

Chapter 6 studies the problem of coordinated freeway ramp metering. An FLC based local coordinative ramp metering strategy is proposed for networked freeway ramp metering. Through information exchange among neighboring local controllers, local measurements on traffic conditions are shared among neighboring controllers. Consequently, reference mainstream densities are generated by FLC based coordinative decision making algorithms based on both local and exchanged measurements. Finally, ALINEA based reference tracking algorithms are utilized to track the reference mainstream densities accordingly. The optimal parameters of the coordinated decision making algorithms are found by SPSA based parameter learning. By the proposed ramp metering strategy, reduced communication cost and system complexity are obtained due to the information exchange scheme among neighboring controllers, and system performance is improved through an parameter learning scheme which works without disturbing the normal freeway operations.

Chapter 7 proposes a novel macroscopic traffic scheduling strategy for addressing the networked freeway ramp metering problem. By regarding freeway traffic as a stochastic process which is generally repeated, traffic flow within the freeway network is scheduled at the macroscopic level, where the reference mainstream density signals within macroscopically predefined time periods are scheduled. The ALINEA based algorithm is utilized by local ramp metering controllers to track the scheduled reference signals. The optimal scheduling plan is obtained using an SPSA based model-free parameter learning scheme. The proposed strategy is simple and efficient due to the combination of fixed-time macroscopic traffic scheduling strategy, ALINEA based traffic responsive strategy and the model-free parameter learning scheme.

Chapter 8 comprises conclusions as well as recommendations for future research works.

1.5 Main Contributions

In detail, the results of this present study may shed light on:

- parameter calibration for macroscopic freeway traffic flow model by a proposed novel hybrid iterative calibration algorithm, which accurately estimates parameters of macroscopic traffic flow model and minimizes the discrepancies between real traffic data and model generated traffic data.

- optimal freeway local ramp metering using FLC and microscopic traffic simulation based optimization, which finds the optimal ramp metering strategies and pursues a balance between traffic on the freeway mainstream and on-ramp links.

- FLC based algorithms for local and coordinated freeway ramp metering, which incorporates human expert knowledge in controller design and effectively cope with the randomness and uncertainties in freeway system .

- efficient realtime parameter learning for optimal freeway ramp metering, which improves the system performance by learning from historical data to direct parameter updating without a priori knowledge on system dynamics.

- optimal ramp metering for networked freeway system by macroscopic traffic scheduling , which combines the simple fixed-time traffic scheduling strategy with the efficient ALINEA based traffic responsive strategy to provide simple but efficient solution for networked freeway ramp metering problems.

- coordinated freeway ramp metering using FLC based local coordinative ramp metering strategy, which complements the drawbacks of centralized control systems with reduced communication cost and improved system performance.

The contributions of the thesis are summarized in Tab. 1.2.

Problem	**Challenges**	**Method**	**Para Tuning**	**Performance**
Parameter calibration: Chapter 3	A: Nonlinear dyn, sys noise and distb	Multivariate N-R with SP	Guaranteed accurate conv, improved local minima avoidance	Consistently minimized CF
Local RM: Chapter 4 & 5	B: A and traffic balance issue, uncertainties	FLC with P-SO tuning	Efficient	Effective reduction of CF, well balanced freeway traffic
		FLC with SP-SA tuning	Simple and effective	Efficient minimization of CF, well balanced freeway traffic, realtime implementable
Networked RM: Chapter 6 & 7	C: B and complex inter-controller coupling	FLC based LCRM with SPSA tuning	Simple and effective	Effective reduction of CF, low communication and implementation cost, realtime implementable
		MTS with SPSA tuning	Simple and effective	Efficient minimization of CF, simple system structure, low implementation cost, minor or no communication

Tab. 1.2: The contributions of the thesis. para: parameter, dyn: dynamics, sys: system, distb: disturbance,N-R: Newton-Raphson, FLC: fuzzy logic control, SP: simultaneous perturbation, conv: convergence, CF: cost function, i.e. discrepancy between model generated and real traffic data in parameter calibration or WTTS/TTS in ramp metering, RM: ramp metering, SPSA: simultaneous perturbation stochastic approximation, LCRM: local coordinated ramp metering, MTS: macroscopic traffic scheduling.

Chapter 2

Revisit on SPSA, FLC, METANET and ALINEA

To facilitate the understanding of this thesis, this chapter revisits the SPSA algorithm, the FLC algorithm and the METANET model, which are frequently referred in the subsequent chapters.

Specifically, the SPSA algorithm is adopted as a benchmark parameter calibration algorithm. It is also used for parameter tuning purposes to improve the efficiencies of various ramp metering systems. FLC is used as an intelligent control algorithm for approximation of the optimal control policies, the parameters in the antecedent and consequent parts of the FLC algorithms proposed in this thesis are treated as tunable parameters. The macroscopic freeway traffic flow model, METANET, is used as the default traffic simulation model for case studies. The ALINEA algorithm is regarded as a benchmark ramp metering algorithm.

2.1 The SPSA Algorithm

Simultaneous perturbation stochastic approximation (SPSA) is a type of stochastic approximation (SA) algorithm proposed by Spall [67], for optimizing systems of multiple unknown parameters. SPSA based optimization iteratively update the estimated parameters towards better performing directions by making use of a stochastically estimated gradient information. Different from earlier SA algorithms like RobbinsCMonro algorithm [68], Kiefer-Wolfowitz algorithm [69], the SPSA algorithm requires less computational power in each iteration for parameter updating. This unique feature of SPSA makes it especially useful in dealing with optimization problems with a large number of parameters.

Denote L as a scalar cost function which is related with decision parameters $\boldsymbol{x} \in \mathbb{R}^{p\times 1}$, where p is the number of parameters. The SPSA algorithm for minimization of L is expressed as:

$$\hat{\boldsymbol{x}}_{i+1} = \hat{\boldsymbol{x}}_i - a_i\hat{\boldsymbol{g}}_i \tag{2.1}$$

$$\hat{\boldsymbol{g}}_i\,[j] = \frac{L(\hat{\boldsymbol{x}}_i + c_i\boldsymbol{\delta}_i) - L(\hat{\boldsymbol{x}}_i - c_i\boldsymbol{\delta}_i)}{2c_i\boldsymbol{\delta}_i\,[j]} \tag{2.2}$$

where $i \in [0\ \infty]$ is the index of iteration, $\hat{\boldsymbol{x}}_i$ is the estimation of the optimal parameters at iteration i, c_i denotes a perturbation gain, $\boldsymbol{\delta}_i$ denotes a random vector whose components are Bernoulli distributed on $\{+1, -1\}$ with probability 0.5, $\hat{\boldsymbol{g}}_i\,[j]$ and $\boldsymbol{\delta}_i\,[j]$ denote the jth component of vectors $\hat{\boldsymbol{g}}_i$ and $\boldsymbol{\delta}_i$ respectively.

Values of $L(\hat{\boldsymbol{x}}_i + c_i\boldsymbol{\delta}_i)$ can be observed either from experiments or from simulations. It is worth noting that observations on L are contaminated by various system noises in experiments and realistic simulations, the superiority of SPSA and other SA algorithms is that parameter updating can be carried out to reduce the cost function values, even if strong noise exists in the observations of cost functions values.

Using SPSA based parameter tuning algorithm, the convergence of parameters to the global optimal is subject to satisfactions of several assumptions on the considered system and the configurations of algorithmic parameters [67]. The important conditions required on a_i and c_i are as follows:

1. $a_i > 0$, $a_i \to 0$ as $i \to \infty$, and $\sum_{i=0}^{\infty} a_i = \infty$

2. $c_i > 0$, $c_i \to 0$ as $i \to \infty$, and $\sum_{i=0}^{\infty}(\frac{a_i}{c_i})^2 < \infty$

Note that no system model information is required in the implementations of SPSA algorithm, which means that SPSA is a model-free optimization algorithm. This feature of SPSA is important for real implementations, because explicit relationship between the system cost function ,L, and the system parameters, $\boldsymbol{\theta}$, is hardly available in complex and large scale systems. The algorithmic structure of the SPSA algorithm is also very simple, i.e. no complex mathematical operation is involved. These features of the SPSA algorithm make it quite suitable for solving realtime optimization problems.

2.2 The FLC Algorithm

Fuzzy logic began with the 1965 proposal of fuzzy set theory by Lotfi Zadeh [70], which is a form of multiple-valued logic. It emulates the human brain's reasoning mechanism, where representation of information and knowledge is approximate rather than fixed and exact. In contrast with traditional logic, by which binary sets have two-valued logic, true or false, fuzzy logic variables may have a truth value that ranges in degree between 0 and 1. Fuzzy logic handles the concept of partial truth, where the degree of truth may range between completely true and completely false. Furthermore, when linguistic variables are used, these degrees may be managed by specific functions. Fuzzy logic has been applied to many fields, from control theory to artificial intelligence.

In this work, a T-S type fuzzy logic controller (FLC) based algorithm is used for freeway local ramp metering. Fuzzy labels are defined for input variables and fuzzy rules are designed to determine the controller output by linear equations. The "IF-THEN" fuzzy rules emulate the reasoning and thinking mechanism of human brain, which is convenient for incorporation of human expert knowledge in controller design. The mechanism of fuzzy logic control is summarized in Fig. 2.1. For each input vector, membership values of all input variables are calculated with respect to their fuzzy sets, this step is named as "FUZZIFICATION". Consequently, the firing weights of each fuzzy rule is determined according to the membership values of input variables with respect to the corresponding fuzzy sets in each rule, and this step is referred as "INFERENCE". The final output of the controller is the sum of outputs of all rules weighted by the corresponding firing weights, referred as "DEFUZZIFICATION".

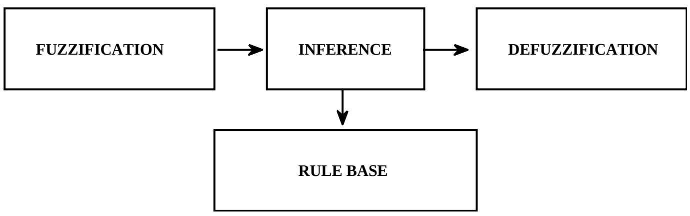


Fig. 2.1: Flow chart of fuzzy logic control.

Denote x_m, $m \in [1, M]$ the mth input variable, where M is the number of input variables, denote $L^l(x_m)$ the linguistic variable of x_m corresponding to the lth fuzzy rule, an example fuzzy rule is expressed as:

$$IF\ x_1 \text{ is } L^l(x_1)\ AND\ x_2 \text{ is } L^l(x_2) \cdots\ AND\ x_M \text{ is } L^l(x_M),$$
$$THEN\ y^l = \theta_0^l + \theta_1^l x_1 + \cdots + \theta_m^l x_m,$$

where θ_j^l, $j \in [0, M]$ are all constant parameters, l denotes the index of the fuzzy rule and y^l denotes the rule output.

Denote $\mu^l(x_m)$ the membership value of x_m with respect to input fuzzy set $L^l(x_m)$, the firing weight of the above fuzzy rule, denoted as μ^l, is calculated as:

$$\mu^l = min(\mu^l(x_1), \mu^l(x_2), \cdots, \mu^l(x_M)) \tag{2.3}$$

or

$$\mu^l = \mu^l(x_1) * \mu^l(x_2) * \cdots * \mu^l(x_M) \tag{2.4}$$

depending on the the inference mechanism used.

The final output y is then calculated by the following formula:

$$y = \frac{\sum_l \mu^l y^l}{\sum_l \mu^l}. \tag{2.5}$$

2.3 The METANET Model

Freeway traffic flow behavior is highly complex which can be described by a set of highly nonlinear equations [1, 2, 5, 23]. Among these models, the METANET model is most widely used [5]. In METANET model, the freeway mainstream link is divided into small sections, where each section can be connected with an on-ramp and/or off-ramp link. An illustrative example of the section model is given in Fig. 2.2. The complete model describes the spatial and temporal relationships between the main state variables, i.e. average mainstream density, speed, and flow, and the main mathematic equations involved are as follows:

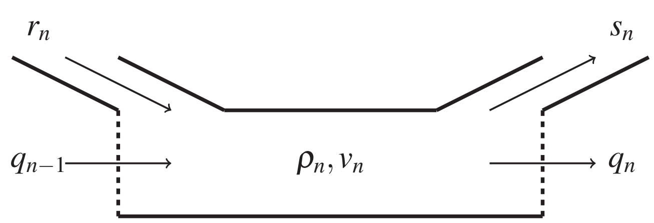


Fig. 2.2: Freeway mainstream section model.

$$\rho_n(k+1) = \rho_n(k) + \frac{T}{L_n}[q_{n-1}(k) - q_n(k) + r_n(k) - s_n(k)] \tag{2.6}$$

$$q_n(k) = \rho_n(k)v_n(k) \tag{2.7}$$

$$\begin{aligned} v_n(k+1) = v_n(k) &+ \underbrace{\frac{T}{\tau}\left[V\left(\rho_n(k)\right) - v_n(k)\right]}_{\text{relaxation term}} \\ &+ \underbrace{L_n v_n(k)\left[v_{n-1}(k) - v_n(k)\right]}_{\text{convection term}} \\ &- \underbrace{\frac{T\mu}{L_n\tau}\frac{[\rho_{n+1}(k) - \rho_n(k)]}{[\rho_n(k) + \psi]}}_{\text{anticipation term}} \end{aligned} \tag{2.8}$$

$$V\left(\rho_n(k)\right) = v_f\, exp\left(-\frac{1}{a}(\frac{\rho_n(k)}{\rho_c})^a\right), \tag{2.9}$$

where the variables are defined as:

n index of mainstream sections, $n \in [1, N]$ and N is the total number of mainstream sections;

k index of discrete time step, $k \in [0, K]$ and K is the total number of time steps;

T period of sampling ($hour$);

ρ_n average density within section n, (veh/km);

v_n mean speed of vehicles within section n, ($km/hour$);

q_n volume of vehicles from section n to $n+1$, ($veh/hour$);

r_n inflow volume of vehicles at on-ramp of section n, ($veh/hour$);

s_n outflow volume of vehicles at off-ramp of section n, ($veh/hour$);

v_f free flow speed of vehicles, the speed of vehicles under zero mainstream density, ($km/hour$);

ρ_c the critical mainstream density, (veh/km);

L_n length of section n, (km);

τ a time constant, reflecting the reaction speed of drivers, $(hour)$;

μ, ψ, and a are all constant parameters, reflecting the characteristics of geometry of freeway roads, vehicle types and driver behaviors. (2.6) is the density equation which shows the conservation law of vehicles. (2.7) expresses the relationship between average traffic flow, density and space mean speed. (2.8) is the equation that determines the speed variation from k to $k+1$. The speed variation is determined by three terms: the relaxation term showing that mainstream traffic speed intends to follow a target value determined by the fundamental relationship between density and speed under homogeneous traffic conditions, the convection term showing contribution of upstream section traffic to the speed dynamics, and the anticipation term reflecting influence of downstream traffic to speed dynamics of the current section. Note that exponential nonlinearity exists in (2.9), the last three terms and (2.7) are all nonlinear, making the complete model complexly parameterized by the following model parameters

$$\boldsymbol{\theta} = [v_f \ \rho_c \ a \ \mu \ \psi \ \tau]^T .$$

The evolution of queue volume on the on-ramp links is described by:

$$\omega(k+1) = \omega(k) + T(d(k) - r(k)), \tag{2.10}$$

where $d(k)$ denotes the flow rate of traffic demand at the on-ramp link.

Additional terms can be added to (2.8) to capture the impact of merging flow and lane drop to mean traffic speed on the mainstream link [71].

2.4 The ALINEA Algorithm

ALINEA is the most well-known ramp metering algorithm which was proposed by Markos Papageorgiou in the 1990s. The ALINEA control law is expressed as:

$$r(k+1) = r(k) + \beta(o^* - o(k)). \tag{2.11}$$

The flow rate of merging traffic should not exceed the maximum traffic flow available at the on-ramp link, where the maximum flow rate is calculated as:

$$r^{\omega}_{max}(k+1) = d(k) + \frac{\omega(k)}{T}. \tag{2.12}$$

An additional constraint is imposed on the maximum allowable flow rate from the on-ramp link due to considerations of traffic condition in the mainstream. This constraint is calculated as:

$$r^{o}_{max} = Q_o \frac{\rho_{max} - \rho(k)}{\rho_{max} - \rho_c}, \tag{2.13}$$

where Q_o is the maximum flow rate achievable on the on-ramp link under free-flow conditions, and ρ_{max} is the maximum density on the mainstream. To prevent the ramp metering signal from exceeding these physical limit of ramp flow rate, a modified ALINEA algorithm with constraint on the overall ramp metering signal is expressed as:

$$r^1(k+1) = \max\{\min[r(k) + \beta(o^* - o(k)),\ r_{\max}(k+1)],\ r_{\min}\}, \tag{2.14}$$

where $r_{\min}$ is set to be a nonzero value to prevent total closeup of the on-ramp entry, and $r_{\max}(k+1) = min\{r^{\omega}_{max}(k+1), r^{o}_{max}(k+1)\}$ is the maximum allowable flow rate. More detailed settings on constraints of ramp metering signal were discussed [28].

To prevent the formation of high queue volume on the freeway on-ramp link and improve the equity of freeway ramp metering, constraints can be enforced to prevent the queue volume from exceeding predefined limits. Denote ω_{max} as the limit on queue volume, ALINEA ramp metering with queue constraints can be expressed as:

$$\begin{aligned} r(k+1) &= max\{r^1(k+1),\, r^\omega(k+1)\} \\ r^\omega(k+1) &= d(k) - \frac{\omega_{max} - \omega(k)}{T}. \end{aligned} \tag{2.15}$$

Detailed explanation on ramp metering and queue constraints strategies are discussed in [35]

In the next chapter, the hybrid iterative parameter calibration algorithm will be presented.

Chapter 3

Hybrid Iterative Parameter Calibration Algorithm for Macroscopic Freeway Modeling

3.1 Introduction

Freeway traffic is an important subarea in modern intelligent transportation systems, and what measures to take to address the emerging environmental and societal issues caused by traffic congestions has aroused huge interest from researchers. Freeway traffic prediction, travel time estimation and traffic flow control are active topics in this area [5, 7, 28].

Freeway traffic flow is a highly nonlinear process, where there are random traffic demand, uncertain exogenous disturbances and stochastic driver behaviors, and both macroscopic and microscopic traffic models have been studied by researchers to simulate the traffic flow process. Microscopic traffic modeling relies on detailed description of the behaviors of drive-vehicle-unit (DVU) and their interactions, and the environmental factors etc. Macroscopic traffic modeling focuses on describing the evolutions of macroscopic traffic flow state variables. The relationships of the state variables in the time and space domain are expressed by mathematical formulae.

From an engineering perspective of view, first physical principle based macroscopic models are favorable for system analysis and controller design, because conducting model based studies with mathematical formulae is more time and cost efficient compared with experiments and computationally expensive microscopic traffic simulations. A series of fluid dynamics based macroscopic freeway traffic flow models have been studied by researchers [1,2,5,72], and many researches on freeway traffic flow control were carried out based on these models [8,42,71]. To utilize these models, parameter calibration is a prerequisite to ensure accuracy and applicability of the models for specific implementations.

Regarding the parameter calibration problem, a standard practice is to formulate it as a least squares problem by adopting a mean square error (MSE) based cost function to measure the discrepancy between model generated data and real traffic data, and parameters minimizing the cost function are pursued. A heuristic complex algorithm was used to minimize a least square output error based criterion and real freeway data is used for parameter calibration and model validation [23]. However, parameters calibrated by this method may converge to non-stationary points [24,25]. An iterative learning based algorithm was proposed for parameter identification of a macroscopic traffic flow model, where parameter values are regarded as time varying and parameters that led to accurate fitting between model generated data and real data were pursued [73]. However, application of the method to real freeway data needs further investigation. An extended kalman filtering algorithm was proposed for freeway state estimation, where parameters of the METANET model were regarded as part of the system variables and were estimated together with the real freeway state variables [8]. An alternative method for such problem is to recursively update the parameters towards their optimal values by stochastic approximation, e.g. simultaneous perturbation based stochastic approximation (SPSA) [67]. Under several assumptions and conditions, the convergence of parameters to their optimal values is guaranteed [67, 74–76]. This method is especially useful for problems with a large number of decision parameters.

Gradient based algorithms are efficient in solving nonlinear equations, for example, the Newton-Raphson method iteratively update the estimated solutions by utilizing the inverse of analytically calculated Jacobian matrices, where the convergence of parameters is theoretically guaranteed [77] for quite generic nonlinear objective functions that might be non-convex. A potential drawback of gradient based algorithms is to have local minima. The SPSA algorithm estimates the system gradient by randomly producing a set of searching directions, hence increases the chance of escaping from local minima [67]. A limitation of SPSA algorithm is its strict convergence condition, which cannot be easily guaranteed for nonlinear objective functions that are non-convex.

To ensure the convergence of parameters, system gradient information is a critical factor. If the cost function is a scalar one, as is usually the case in optimization problems, the system gradient is in the form of $p \times 1$ gradient vector, where p is the dimension of parameters. It is difficult to ensure the convergence of parameters by existing iterative parameter updating laws when highly nonlinear relationship exists between parameters and the cost function. For instance, the Newton-Raphson method requires the inverse of Jacobian, whereas a vector-valued gradient or its pseudo-inverse is difficult to meet the ranking condition. By introduce multiple cost functions, a Jacobian matrix with full rank can be computed for iteratively updating parameters.

In this chapter, a novel hybrid iterative parameter calibration approach is proposed to calibrate the parameters of macroscopic traffic flow models. The MSE values for multiple data sets are used as cost functions to measure the discrepancies between model generated data and real traffic data, and the objective is to seek parameters that minimize these cost functions. A multivariate Newton-Raphson method based algorithm is adopted to iteratively update the estimated parameters, where the system Jacobian matrix is estimated by a simultaneous perturbation based gradient estimation algorithm. By imposing random perturbations on the parameters, the system Jacobian matrix is estimated based on the corresponding changes in the cost functions according to simple formula. Since the Jacobian matrix estimated from simultaneous perturbation method are randomized, the multivariate Newton-Raphson method based iterative parameter updating law is able to randomly search the parameter space, which reduces the risk of being trapped in local minima.

Simulation studies with real freeway data show that the proposed algorithm is effective in finding parameters of the macroscopic traffic flow model to significantly reduce the discrepancies between model generated data and real freeway data sets. As compared with the SPSA based parameter calibration algorithm, the cost functions obtained by the proposed method are $a\%$ and $b\%$ lower for two sets of real traffic data.

This chapter is organized as follows. The problem of parameter calibration for freeway traffic flow model is formulated in Section 3.2. The hybrid iterative parameter calibration approach is described and analyzed in Section 3.3. Simulation studies are provided in Section 3.4. Section 3.5 concludes the chapter.

3.2 Problem Formulation

The METANET model is adopted for macroscopic modelling of freeway traffic flow in this chapter. Given a stretch of freeway mainstream link with mainstream speed measured at certain location for T consecutive time intervals, given proper boundary conditions, input data and the parameters $\boldsymbol{\theta}$ to the freeway model, the mainstream speed corresponding to the measured location is generated. Denote the set of measured sample mainstream speed sequence and model generated mainstream speed sequence as $\{v_k^s\}$ and $\{v_k^m\}$ respectively, where $k \in [1, T]$ is the index of sample data.

A mean squared errors (MSE) based cost function is used to measure the discrepancy between $\{v_k^m\}$ and $\{v_k^s\}$. Denote the cost function with respect to $\boldsymbol{\theta}$ as $L(\boldsymbol{\theta})$:

$$L(\boldsymbol{\theta}) = \frac{1}{T}\sum_{k=1}^{T} (v_k^s - v_k^m)^2 \,. \tag{3.1}$$

Assume we have o sets of sample data, denote the performance index with respect to these sample sets as

$$\boldsymbol{L}(\boldsymbol{\theta}) = [L_1 \;\cdots\; L_o]^T,$$

which is adopted as the cost function in this work.

The objective of parameter calibration is to find $\boldsymbol{\theta}_*$ that minimizes $\boldsymbol{L}$. Due to the natural model approximation, perfect fitting between sample data and model generated data is impossible. The objective in this work is to find a set of parameters, $\boldsymbol{\theta}_*$, that reduce the cost functions to their minimums $\boldsymbol{L}_*$, i.e. $\boldsymbol{L}_* = \boldsymbol{L}(\boldsymbol{\theta}_*)$. The problem formulated above is equivalent to solving the following nonlinear equations:

$$\boldsymbol{L}(\boldsymbol{\theta}) = \boldsymbol{L}_*. \tag{3.2}$$

It is worth noting that the model parameters can be regarded as both time varying and time invariant; however, parameters identified in this chapter are regarded constant, because the parameters resulted in such a way reflect the characteristics of traffic flow behaviors at the macroscopic level, i.e. the traffic flow dynamics are generalized by a traffic flow model with the same set of parameters.

3.3 Hybrid Iterative Calibration Approach

3.3.1 Simultaneous Perturbation Based Gradient Estimation

To acquire the system gradient, the Jacobian matrix is estimated by a simultaneous perturbation algorithm [67,75], which calculate the system gradient by imposing random perturbations to estimated parameters and observe the variations in cost functions. The simultaneous perturbation algorithm is expressed as:

$$\hat{J}\left[mn\right] = \frac{1}{Z}\sum_{z=1}^{Z}\frac{L_m\left(\hat{\boldsymbol{\theta}} + c\boldsymbol{\Delta}^z\right) - L_m\left(\hat{\boldsymbol{\theta}} - c\boldsymbol{\Delta}^z\right)}{2c\delta_n^z}. \tag{3.3}$$

where $z \in [1,\, Z]$ is the index of perturbation trials, $\hat{\boldsymbol{\theta}}$ is the estimation of $\boldsymbol{\theta}_*$, $\hat{J}\left[mn\right]$ is the component of $\hat{J}$ at the mth row and nth column, $\boldsymbol{\Delta}^z = \left[\delta_1^z \;\cdots\; \delta_n^z \;\cdots\; \delta_p^z\right]^T$ is the perturbation vector corresponding to the zth perturbation trial, c is a positive scalar, which determines the amplitude of perturbation on the parameters.

Denoting $\mathcal{O}(x^n)$ as the order of magnitude at x^n. Assume that the third order derivatives of $\boldsymbol{L}$ exist continuously and are bounded, it can be proved that the expectation of the difference between the Jacobian matrix, J, and the estimated Jacobian matrix, $\hat{J}$, by simultaneous perturbation algorithm given in (3.3) is $\mathcal{O}(c^2)$, i.e.

$$J\left[mn\right] - \hat{J}\left[mn\right] = \mathcal{O}\left(c^2\right), \tag{3.4}$$

and this difference is negligible if c is sufficiently small. A complete proof for such problems is given in [67].

3.3.2 The Hybrid Algorithm

Denoting

$$\begin{aligned}
\boldsymbol{L}_i &= \boldsymbol{L}\left(\hat{\boldsymbol{\theta}}_i\right) \\
d\boldsymbol{L}_i &= \boldsymbol{L}_{i+1} - \boldsymbol{L}_i \\
d\boldsymbol{\theta}_i &= \hat{\boldsymbol{\theta}}_{i+1} - \hat{\boldsymbol{\theta}}_i \\
\delta\boldsymbol{L}_i &= \boldsymbol{L}_* - \boldsymbol{L}_i \\
\delta\boldsymbol{\theta}_i &= \boldsymbol{\theta}_* - \hat{\boldsymbol{\theta}}_i \\
\hat{J}_i &= \hat{J}\left(\hat{\boldsymbol{\theta}}_i\right).
\end{aligned}$$

In the following, let $\|\cdot\|$ denote the maximum norm for vectors and its induced matrix norm for matrices.

The proposed hybrid iterative parameter calibration algorithm is expressed as follows:

$$\hat{\boldsymbol{\theta}}_{i+1} = \hat{\boldsymbol{\theta}}_i - a_i \hat{J}_i^{-1} \boldsymbol{L}_i \tag{3.5}$$

where i denotes the iteration number, $\hat{J}_i$ denotes the estimation of the Jacobian matrix by (3.3) and a_i denotes a learning rate.

The proposed algorithm takes the form of multivariate Newton-Raphson algorithm except that the analytical Jacobian matrix is replaced by the estimated Jacobian matrix $\hat{J}$ resulted from simultaneous perturbation method. $\boldsymbol{L}_i$ is cost functions at iteration i, which represents the discrepancies between model generated data and real data for the data sets. From the perspective of learning control theory, the proposed parameter updating algorithm (3.5) can be regarded as a gradient based parameter updating scheme that iteratively learns from the current discrepancies corresponding to the estimated parameters.

It should be noted that the rank of the Jacobian matrix is related to the data sets used, for example, if two sets of data are collected under similar conditions and the MSE values with respect to these two data sets are used as performance indices, the derivatives of the performance indices with respect to the model parameters will be approximately the same. This makes the corresponding rows in the Jacobian matrix strongly correlated and reduce the rank of the Jacobian matrix. Due to the above reason, the data sets used should be weakly correlated from each other, i.e. data should be collected from different locations or on different dates.

3.3.3 Convergence Analysis

The convergence of the proposed algorithm is given in *Theorem* 3.1.

Theorem 3.1. *Given $\boldsymbol{\theta}$ and $\boldsymbol{L}$ as previously defined, the updating law (3.5) guarantees that $\hat{\boldsymbol{\theta}}_i$ and $\boldsymbol{L}_i$ converge to bounded neighborhoods of $\boldsymbol{\theta}_*$ and $\boldsymbol{L}_*$ respectively, i.e.:*

1. $\lim_{i\to\infty} \delta \boldsymbol{L}_i = \frac{\epsilon_1}{1-\rho_1}$,

2. $\lim_{i\to\infty} \delta \boldsymbol{\theta}_i = \frac{\epsilon_2}{1-\rho_2}$,

under conditions that $\rho_1 < 1$ and $\rho_2 < 1$, where ρ_1, ρ_2, ϵ_1 and ϵ_2 are as defined in the proof.

Proof. See **Appendix** 8.2. □

In real implementations, the parameter calibration task becomes much more complex due to the impact of measurement noise, process randomness and exogenous disturbances. Under such conditions, there will be a mismatch between sample and model generated data, which weaken the accuracy of Taylor approximation and the convergence of parameters. To cope with the above issues, gradient estimation can be conducted in a stochastic manner. Firstly, perturbation vectors $\boldsymbol{\Delta}^z$, $z \in [1, p]$ are generated randomly, which satisfy

$$rank([\boldsymbol{\Delta}^1 \ \boldsymbol{\Delta}^2 \ \cdots \ \boldsymbol{\Delta}^p]) = p$$

. Then the system gradient is calculated using the following formula:

$$\hat{J}\,[mn] = \frac{1}{p} \sum_{z=1}^{p} \frac{L_m\left(\hat{\boldsymbol{\theta}} + c\boldsymbol{\Delta}^z\right) - L_m\left(\hat{\boldsymbol{\theta}} - c\boldsymbol{\Delta}^z\right)}{2c\delta_n^z}, \tag{3.6}$$

where $\boldsymbol{\Delta}^z$, $z \in [1,\, p]$ are uncorrelated, which is essential to remove the redundancies within the perturbations to parameters. Additionally, restriction criterion are applied to prevent inappropriate parameter updating, e.g. updating that leads to violent changes in parameters and cost functions. The complete parameter calibration process with restriction criterion is shown in Fig. 3.1. In the above algorithm, checking the rank of

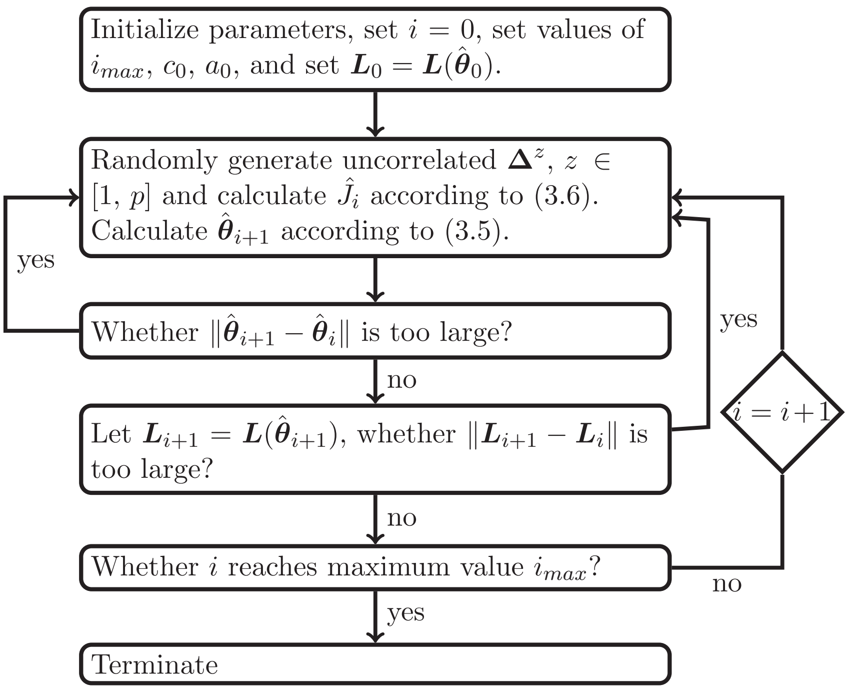


Fig. 3.1: The hybrid iterative calibration algorithm.

$\hat{J}_i$ is to ensure that the ranking condition is satisfied to ensure convergence. Parameter updating resulting in abrupt changes in the parameters and performance indices are prohibited for stability considerations. The implementation of restriction criterion is mainly out of practical considerations to prevent violent variations of parameters.

3.4 Illustrative Examples

3.4.1 Description of Data

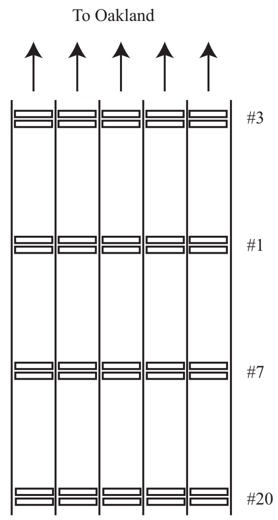


Fig. 3.2: Layout of California I-880 freeway detectors.

Real traffic data on the California I-880 freeway from the PATH programm is used for testing the proposed algorithm. Detailed description on the traffic data is available online (`http://ipa.eecs.berkeley.edu/~pettyk/FSP/`). Measurement data obtained from four sets of mainstream loop detectors is used. A description of the considered freeway and layout of detector stations is given in Fig. 3.2. Data collected from northbound detectors at detector stations numbered 3, 1, 7 and 20 on the California I-880 freeway is used. Detectors are allocated at an interval of 1700 feet. The original freeway data is processed with a 1 minute time interval. This data is further discretized with 15-seconds interval by linear interpolation, because a time interval of 15 seconds is considered suitable for freeway traffic modeling when the interval length of detectors is around 500

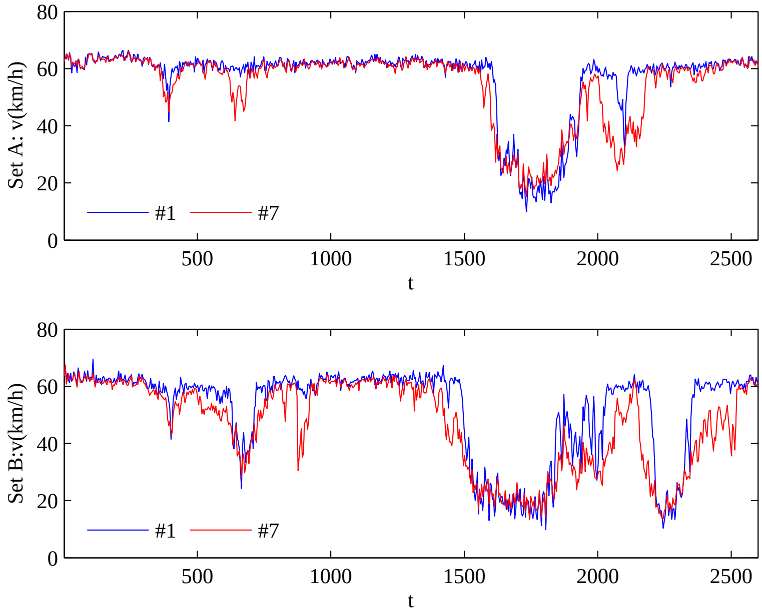


Fig. 3.3: Speed profiles of real data at detector station 1 and 7.

meters (1700 feet) [23]. 2633 data points in total are resulted from the interpolation from each measurement station. Let x_{t_1} and x_{t_2}, $t_2 > t_1$, denote the original data consecutively measured at time t_1 and t_2, three new data points are obtained by the following linear formula:

$$x_{t_i} = x_{t_1} + \frac{i}{4} \times (x_{t_2} - x_{t_1}), i \in \{1,\ 2,\ 3\}. \tag{3.7}$$

In the simulations, two sets of data collected from two different days are used. For convenience, the two sets are denoted as A and B in the following. Since data collected from detector stations 3 and 20 are used as input to the METANET model, model generated data at detector stations 1 and 7 is regarded as output of the model. The speed profile of the real data measured at detector stations 1 and 7 are given in Fig. 3.3. #1 and #7 denote the detector stations 1 and 7. Set A is the data set used for parameter calibration and Set B is data set used for validating the calibrated parameters.

3.4.2 Simulation Setup

Denote model generated traffic speed at detector station 1 and 7 as $v_1(t)$ and $v_7(t)$, $t \in [1\ T]$, where T is the total number of data points considered, denote the real traffic speed data at detector station 1 and 7 as $v_1^o(t)$ and $v_7^o(t)$. The following performance indices are defined:

$$\begin{aligned}
L_1 &= (\frac{1}{T}\sum_{t=1}^{T}(v_1(t) - v_1^o(t))^2)^{0.5} \\
L_2 &= (\frac{1}{T}\sum_{t=1}^{T}(v_7(t) - v_7^o(t))^2)^{0.5} \\
L_s &= (\frac{1}{2T}\sum_{t=1}^{T}((v_1(t) - v_1^o(t))^2 + (v_7(t) - v_7^o(t))^2))^{0.5}
\end{aligned} \tag{3.8}$$

In the following, $\boldsymbol{L}_h = [L_1\ L_2]^T$ denotes the performance index vector adopted by the hybrid algorithm. L_s is the performance index adopted by SPSA algorithm, which is actually the MSE with respect to data at both detector stations. A decaying updating gain is adopted by SPSA as suggested [75], i.e. $a_i = \frac{0.015}{(i+1)^{0.602}}$. The updating gain for the hybrid algorithm is a constant one , i.e. $a_i = 0.015$, $\forall i$. The amplitude of perturbations adopted by SPSA is a decaying one, i.e. $c_i = \frac{c_0}{(i+1)^{0.201}}$, as suggested in [75], where c_0 is an initial perturbation amplitude. In both cases, the initial parameter vector is $\boldsymbol{\theta} = [70\ 45\ 3\ 50\ 15\ 0.03]^T$, and $c_0 = [0.5\ 0.5\ 0.2\ 0.5\ 0.5\ 0.005]$. The pseudo inverse of the Jacobian matrix is used in the simulations, because two performance indices are available and the Jacobian matrix not square.

3.4.3 Results And Discussion

In this chapter, data set A is used for parameter calibration and set B is used for validating the calibrated parameters. For convenience, the SPSA based calibration is referred as Case I and the hybrid iterative algorithm based calibration is referred as Case II in the following.

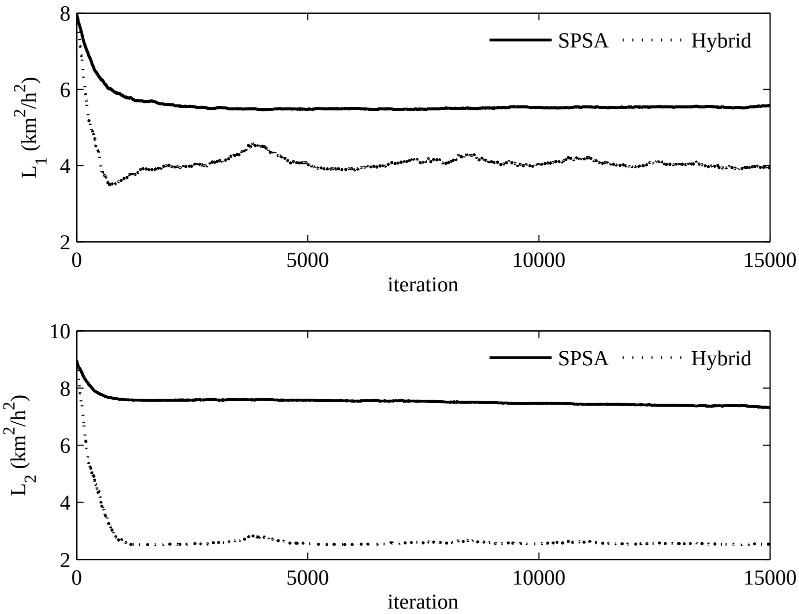


Fig. 3.4: Evolution of performance index values, L_1 and L_2.

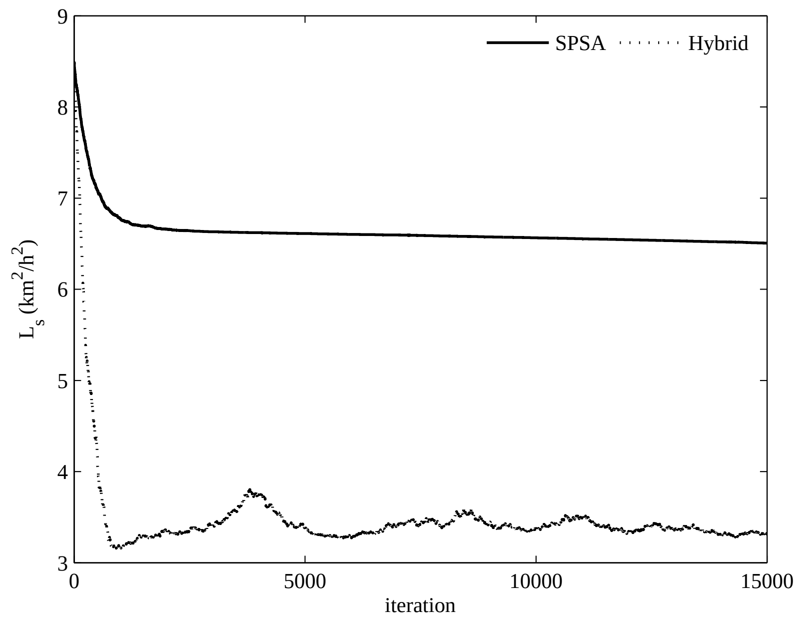


Fig. 3.5: Evolution of L_s.

The evolution of individual cost function values in 15000 iterations are given in Fig. 3.4. As shown, the cost functions are significantly reduced in both Case I and II. The stable values of L_1 and L_2 obtained are 4.974 and 3.458 respectively in Case I, a and b in Case II, where the values obtained by the hybrid method is $A\%$ and $B\%$ lower than that obtained by SPSA. This shows the superiority of the proposed algorithm in achieving more accurate fitting between model generated data and real data. This superiority of the proposed algorithm is further verified from a comparison of the evolution of L_s in Fig. 3.5, where L_s resulted are c and d in case I and II, where a $e\%$ reduction is obtained by the proposed hybrid method.

The rates of convergence in L_1, L_2 and L_s in Case II are faster than that in Case I, showing an advantage of the proposed hybrid algorithm over SPSA; however, it is worth mentioning that this advantage is achieved at the cost of more evaluation trials for the proposed hybrid algorithm than that for the SPSA based algorithm.

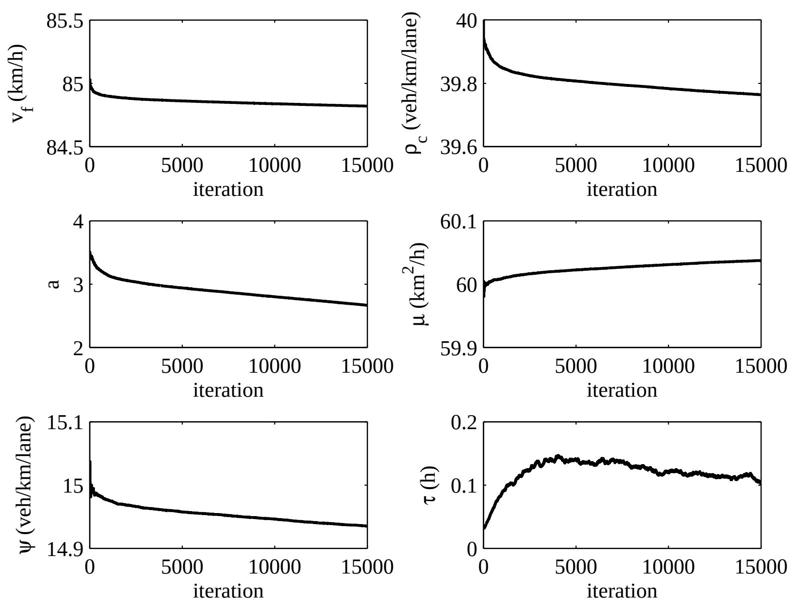


Fig. 3.6: Evolution of parameters in Case I.

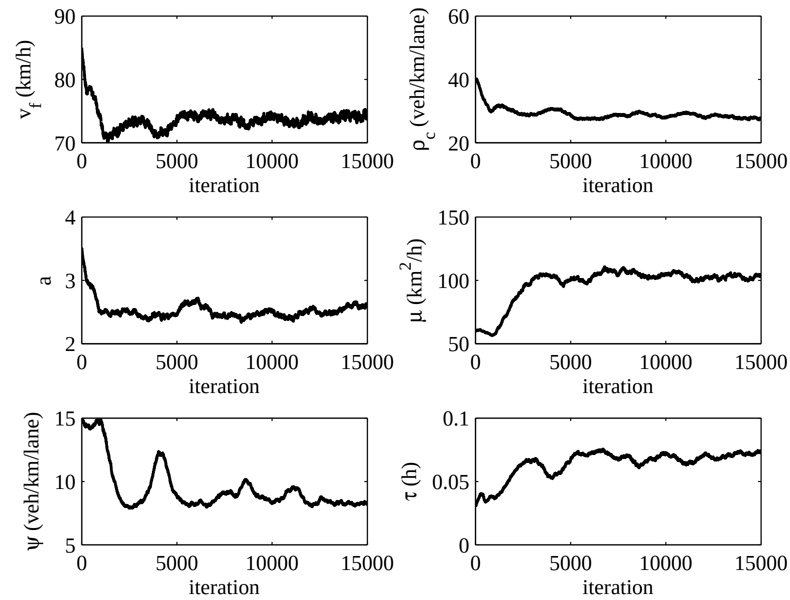


Fig. 3.7: Evolution of parameters in Case II.

The evolution of parameters in Case I and Case II are given in Fig. 3.6 and Fig. 3.7. It can be seen that parameter convergence are achieved in both cases. The directions of parametric updating in Case II vary frequently at the macroscopic level, while parametric updating in Case I follows uniform macroscopic directions for individual parameters. This shows that larger space in the parameter space has been evaluated and considered by the hybrid parameter calibration method, i.e. more updating directions have been searched, which is as expected and helpful for avoiding local minima.

To validate the parameters calibrated, they are used by the METANET model for fitting the validating data. The error between real data and the model generated data at the examined detector stations are given in Fig. 3.8 and Fig. 3.9, where t is the index of data points, $e_{\sharp 1}(t)$ and $e_{\sharp 7}(t)$ are the difference between real data and model generated data at time t and detector stations 1 and 7 respectively. As is shown, the model generated data with parameters calibrated by the hybrid method (red curve) fits

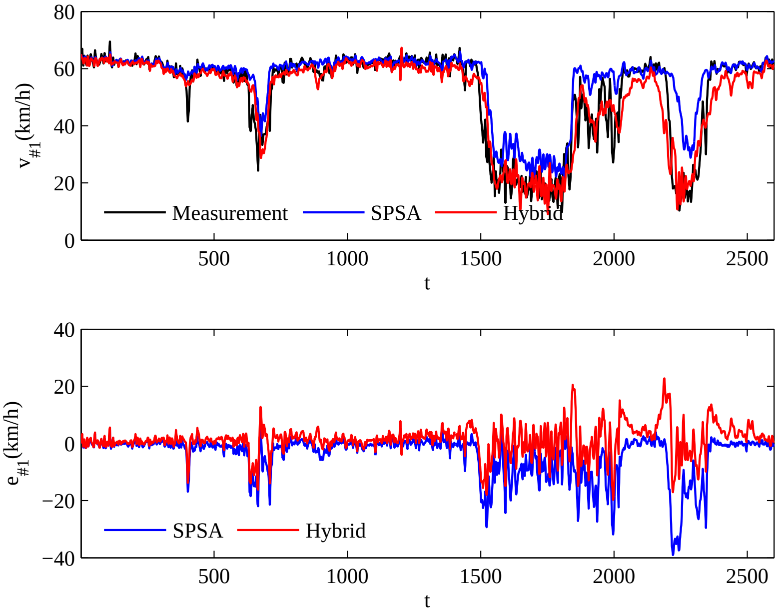


Fig. 3.8: Results of parameter validation.

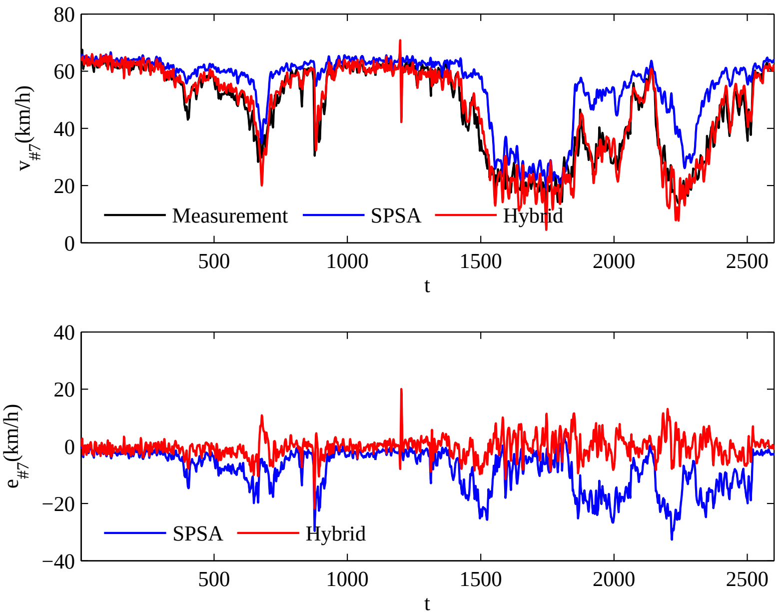


Fig. 3.9: Results of parameter validation.

the measurement data more accurately compared with the SPSA calibrated parameter case. $e_{\sharp 1}(t)$ and $e_{\sharp 7}(t)$ during the time intervals between 1500 and 2500, differ greatly in two cases: these fitting error values fluctuate with smaller amplitudes around zero in the hybrid calibration case, while obvious steady state errors exist in the other case. This indicates that the fitting accuracy is significantly improved by parameters calibrated from the hybrid method. The values of L_1, L_2 and L_s with parameters calibrated from Case I and II are 8.543, 10.722, 9.694 and 5.261, 3.522, 4.477 respectively. The cost function values with respect to detector stations 1 and 7 are greatly reduced when parameters calibrated from the proposed algorithm is used, and the overall RMSE is also considerably lower than that resulted from parameters calibrated by SPSA based algorithm.

The above results clearly demonstrate that the proposed hybrid iterative parameter calibration algorithm is able to achieve very good overall accuracy of fitting between model generated data and real data, and convergence of parameters is improved compared with the SPSA based algorithm.

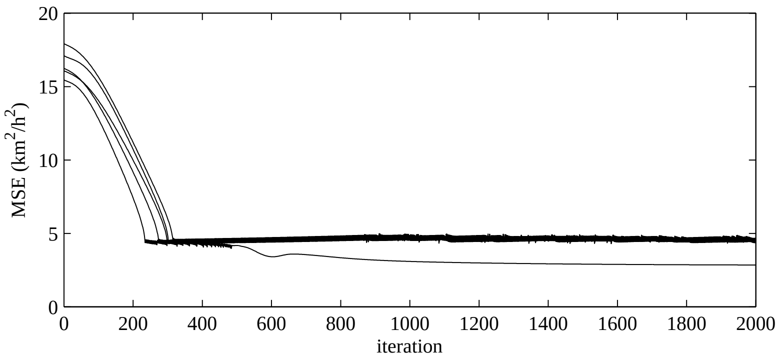
3.4.4 Further Investigation

To obtain the gradient information, a standard operation is to calculate the gradient analytically based on the available system model with respect to real traffic data. However, Newton-Raphson method easily converges to local minimum when the system model is highly complex and multiple local minimum points exists in the parameter space, and parametric convergence is sensitive to the initial parameter values. Due to the randomized perturbation and updating mechanism adopted in the proposed method for gradient estimation, the parameter calibration process are able jump out of the local minima rather than strictly following the directions resulted from local gradient information. Hence the convergence properties can be enhanced by using the proposed gradient estimation instead of analytically calculated gradient.

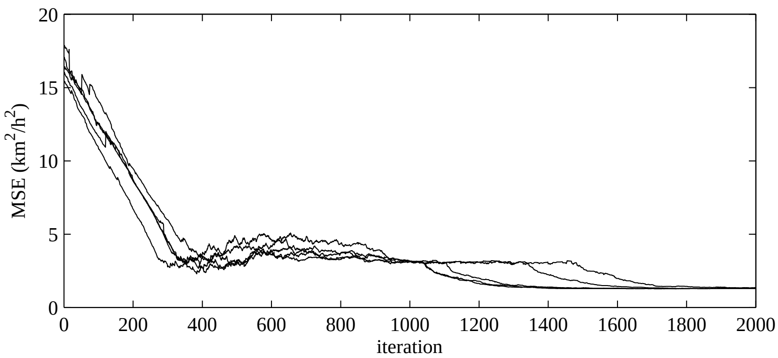
Two groups of calibration tests are conducted to compare the performance of the multivariate Newton-Raphson method using the estimated gradient and analytically calculated gradient. Traffic data collected under free flow and congested traffic conditions are used in test Group A and Group B. The first 100 and first 1000 data sets described in 3.4.2 are considered as collected under free flow and congested traffic conditions, and are used in Group A and B respectively. It is obvious that a traffic congestion occurs during the time intervals from 500 to 1000. In each group, 5 set of initial parameter values are randomly generated. These parameters are consequently used for parameter calibration with gradient analytically calculated and estimation respectively.

The results of test Group A in Fig. 3.10 show that the performance of analytically calculated gradient based calibration is sensitive to the initial values of the parameters, where the MSE values occasionally converge to local minima. In comparison, the hybrid algorithm with randomly estimated gradient performs well for randomly selected initial values, and the MSE values converge uniformly to a value (1.334) which is lower than the minimum (2.846) achieved with analytically calculated gradient. The results of test Group B in Fig. 3.11 show that when traffic data resulted from congestion is used, the gradient estimation based hybrid calibration method performs well, while in the analytical gradient calculation case, the performance is inconsistent with that obtained in Group A and MSE diverges. The inconsistency in the performance of analytical gradient calculation based Newton-Raphson method is possibly due to the nonlinear traffic flow model and highly complex traffic flow dynamics, especially under congestion.

These results demonstrate that the proposed hybrid method with estimated gradient improved the performance of Newton-Raphson method based parameter calibration algorithm by achieving lower cost function and enhanced parametric convergence.



(a) Analytically calculated gradient.

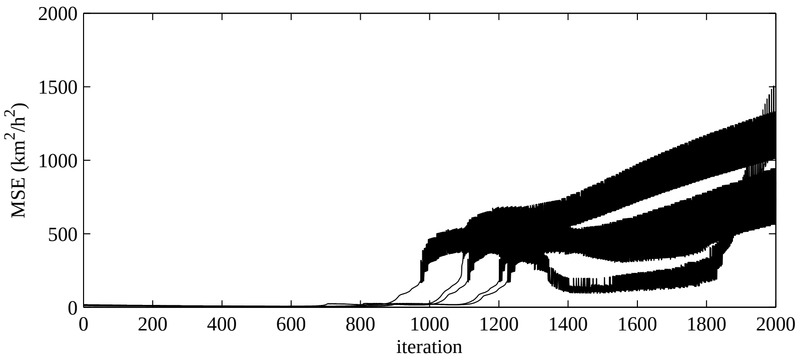


(b) Estimated gradient.

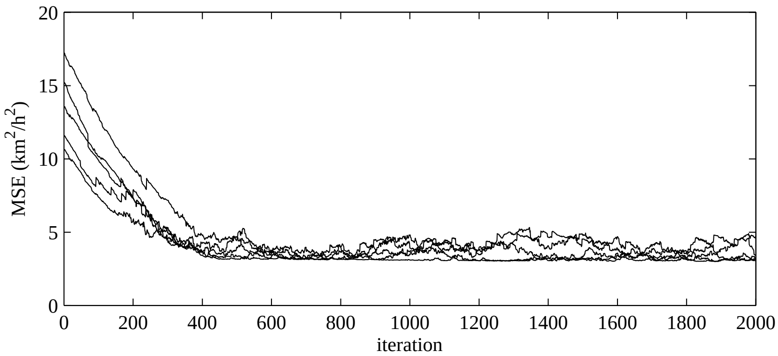
Fig. 3.10: Results of test simulations using traffic data under free flow conditions.

3.5 Conclusion

A novel hybrid iterative parameter calibration approach is proposed for parameter calibration of macroscopic freeway traffic flow models. The parameter calibration problem is formulated as an optimization problem with multiple performance indices. By combination of the iterative multivariate Newton-Raphson method with the simultaneous perturbation based numerical gradient estimation scheme, the performance index values of multiple data sets are driven towards a desired value. By the proposed approach, the fitting accuracies for multiple data sets are investigated and an uniform accuracy level is obtained for all data sets. Numerical studies with real freeway data show that the proposed hybrid approach effectively finds parameters that drive all performance indices



(a) Analytically calculated gradient.



(b) Estimated gradient.

Fig. 3.11: Results of test simulations using traffic data with traffic congestion.

to the desired value, and outperforms the SPSA based parameter calibration algorithm by improved convergence of parameters and higher accuracy of data fitting.

Chapter 3 tackles the parameter calibration problem, which is the basis for model based research on freeway traffic control. By the hybrid parameter calibration algorithm proposed in Chapter 3, the parameters of freeway traffic flow models are accurately calibrated so that the real traffic situations can be well reproduced using the traffic flow model and traffic data. Above all, the work presented in Chapter 3 qualifies us to carry out various research on freeway traffic control using model based simulations with reasonable confidence on the results.

In the remaining chapters, freeway ramp metering at both local and network levels are investigated. In particular, Chapters 5 to 7 are based on simulations using macroscopic traffic flow model. Coming next is a Chapter on freeway optimal local ramp metering using FLC based control algorithm, which is an attempt to utilization of microscopic traffic flow models for assisting the design of ramp metering controllers.

Chapter 4

Optimal Freeway Local Ramp Metering Using FLC and PSO

4.1 Introduction

As traffic demand and traffic congestion rate increase in metropolitan areas around the world, development of freeway infrastructures has greatly increased in past decades. Due to the unavailability of land resource, researchers and practitioners have been motivated to pursue more efficient utilization of existing traffic infrastructures rather than blind construction of new ones.

Various freeway traffic management strategies have been studied. Among these methods, ramp metering has been reported to be efficient in dealing with freeway congestions and improving freeway mainstream traffic flow [26]. A freeway ramp is a section of road which allows vehicles to enter or exit a freeway. An entry ramp is called on-ramp and an exiting ramp is called off-ramp. Ramp metering aims at maintaining proper freeway traffic conditions by regulating the traffic flows entering freeways from the on-ramp entries. Ramp metering is realized by implementation of a device, usually a traffic light or a two-phase (red and green only) signal together with a signal controller at the on-ramp link.

Existing ramp metering algorithms can be categorized into fixed time strategies and real-time (traffic responsive) strategies. Fixed time ramp metering strategies adopt fixed ramp metering signals at specific times and have been plagued with low efficiency [28, 78, 79]. Traffic responsive ramp metering strategies determine ramp metering signals according to realtime traffic conditions. Traffic responsive strategies can be further categorized into the local and coordinated ramp metering algorithms. Local ramp metering determines the ramp metering signals at an on-ramp entry according to traffic conditions at the vicinity of the merging area. The demand-capacity (DC) and its variations determine the ramp flow based on the difference between a predefined mainstream flow capacity and the measured mainstream flow upstream of the merging area [80]. This algorithm was criticized for adopting constant mainstream flow capacity [28]. A number of ramp metering algorithms are based on the famous fundamental diagram, which shows the relationship between mainstream traffic flow and density under homogeneous traffic conditions. As shown in Fig. 1.4, mainstream traffic flow achieves its maximum when density is at the critical value. These algorithms try to maintain the mainstream density at the critical density by ramp metering so as to maximize the mainstream flow. The feedback control based ALINEA algorithm is a well-known ramp metering algorithm. By ALINEA algorithm, the mainstream occupancy (mainstream traffic density) is measured, and the error between the measured occupancy and the critical occupancy (density) value is used to update the ramp metering signal [33].

Coordinated ramp metering aims at optimizing the performance of the network-wide traffic flow, which requires the on-ramps within the network to be controlled in a coordinated manner rather than independently [28,38,81]. Therefore, coordinated ramp metering algorithms determine the ramp metering signals according to traffic conditions of the entire freeway network. Total time spent (TTS) by vehicles within the freeway network is usually adopted as a cost function to measure the efficiency of coordinated ramp metering systems.

Artificial Intelligence (AI) based approaches were also studied for traffic problems. Fuzzy clustering was used for estimation of travel time [43], a type-2 fuzzy logic based approach was proposed for estimation of short term traffic [44], a hybrid fuzzy neural network was proposed for freeway incident detection with linear least square regression [45] and reinforcement learning and multi-agent system based urban traffic control systems were studied [46]. FLC based algorithms were reported beneficial to freeway traffic control with good robustness and smoothness of control signal, and improved traffic conditions through microscopic simulation was reported with FLC based ramp metering [48].

Traffic simulation is important for studies on traffic control, especially for evaluating the efficiencies of traffic control or management algorithms. Microscopic and macroscopic traffic simulation models are commonly used for researches on freeway traffic. Microscopic traffic simulations are based on modeling the behaviors of individual Driver-Vehicle-Unit (DVU) and detailed description of physical and environmental constraints. Microscopic traffic simulations such as PARAMICS and VISSIM have received wide applications. Macroscopic simulation models are comprised of mathematical equations which describe the temporal and spatial relationships among aggregated traffic state variables, i.e. mean traffic density, speed and flow. METANET model is a second order macroscopic freeway traffic flow model which is used in various studies on freeway traffic [5]. However, it was reported that microscopic activities in traffic flow, e.g. interactions among vehicles, greatly influence the traffic flow dynamics, especially under congested traffic conditions [12]. Whether macroscopic models can fully represent the influence of these microscopic activities requires further studies. Since ramp metering controllers are expected to deal with congestions, therefore, more powerful and realistic simulation method would be necessary for validation of the such algorithms.

The objective of ramp metering is another important issue in freeway local ramp metering. Most existing ramp metering algorithms aim at obtaining optimal mainstream flow through maintaining the mainstream density or occupancy at the critical value. Such a method incurs several problems. First, the efficiency of the algorithms depends on estimation of the critical density or occupancy value which is usually defined empirically. In fact it has been revealed that these critical values are time varying and accurate estimation of critical density is still unresolved. Second, the relationship between freeway average mainstream flow and density under inhomogeneous and congested conditions are uninvestigated, which however is the basis of such algorithms in achieving optimal mainstream traffic flow. Third, the time delay incurred by vehicles on the on-ramp link is not discussed while ramp metering aims at maximizing mainstream traffic flow only.

A FLC based ramp metering controller was proposed in [49] where total time spent (TTS) by vehicles within the freeway system is used as the cost function, and a model predictive control based methodology was adopted to tune the controller parameters. The work is limited in the following aspects. First, the traffic conditions within the whole freeway link might not be fully measured by detectors to calculate the TTS, which requires either more detectors or prediction of traffic conditions. Second, the efficiency is highly dependent on the accuracy of the macroscopic traffic flow models. Third, continuous computational power is required for implementation of the proposed algorithm.

In this chapter, we propose a novel T-S type FLC based ramp metering algorithm for solving the optimal freeway local ramp metering problem, and a Weighted TTS (WTTS) based cost function that considers traffic conditions on both the freeway mainstream and on-ramp link. The optimization of the cost function essentially requires maintaining a proper balance between traffic conditions on the mainstream and on-ramp link. An advantage of using WTTS instead of TTS is that the performance of ramp metering can be evaluated without the need to measure or predict the traffic conditions of the entire freeway network. The input membership functions of the FLC controller are predefined, and the size of fuzzy rule base is reduced by incorporating human expert knowledge. Parameters of the consequent part are fine-tuned through a PSO algorithm and microscopic traffic simulations. The microscopic traffic simulation platform, PARAMICS, is used to evaluate controller performance and provides detailed and realistic simulation of traffic flow behaviors.

The chapter is organized as follows. Section 4.2 provides background knowledge and formulation of the optimal freeway local ramp metering problem. Section 4.3 presents the proposed FLC based local ramp metering algorithm and the PSO based parameter tuning algorithm. In Section 4.4, the performance of the proposed algorithm is examined through numerical experiments on PARAMICS simulation platform. Section 4.5 concludes the chapter.

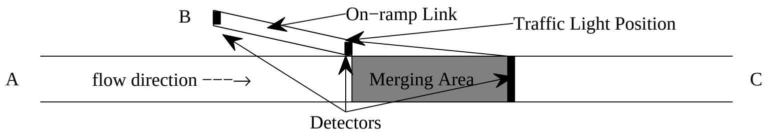


Fig. 4.1: Freeway local ramp metering model.

4.2 Problem Statement

4.2.1 Freeway Model

A freeway mainstream link with an on-ramp link is considered, as shown in Fig. 4.1. Measurement data is collected from detectors on the freeway mainstream and on-ramp link. Mainstream average density (or occupancy), speed and queue length on the on-ramp link can be measured by proper deployment of detectors, i.e. as indicated in the figure. Detectors are deployed on both the mainstream link and on-ramp link. The mainstream merging area is the mainstream area connected to the on-ramp link. A detector is located at the downstream location of the mainstream merging area, thus mainstream traffic condition can be reflected by the measurement from this detector, i.e. mainstream average flow, speed and density (which is equivalently replaced by occupancy in practice). Detectors on the on-ramp link are located at beginning and ending positions so that traffic conditions on the on-ramp link is monitored. Upstream traffic is the mainstream traffic from point A to the merging area, and downstream traffic is the mainstream traffic from the merging area to point C.

Without loss of generality, the dynamics of freeway traffic flow can be characterized by a discrete relationship between freeway states, $\boldsymbol{x}(k) \in \boldsymbol{X}$, and control signal or the ramp metering signal, $r(k) \in \boldsymbol{R}$:

$$\boldsymbol{x}(k+1) = \boldsymbol{f}(\boldsymbol{x}(k),\, r(k)), \tag{4.1}$$

where system states $\boldsymbol{x}(k)$ can include average flows, densities and velocities of mainstream merging area. Ramp metering algorithm can be defined as a set of functions $[\boldsymbol{X} \rightarrow \boldsymbol{R}]$, which define the ramp metering signal, r, according to system states $\boldsymbol{x}$.

The cost function J can be regarded as a functional mapping defined as:

$$J = g(\boldsymbol{x}(k),\, r(k)). \tag{4.2}$$

4.2.2 Objective

By regarding the ramp metering control algorithm as a functional mapping, i.e. $r(k) = h(\boldsymbol{x}(k))$, $h \in [\boldsymbol{X} \rightarrow \boldsymbol{R}]$, the objective of optimal local ramp metering is to seek an optimal function h^* within this set such that the cost function is minimized, i.e.

$$h^* = \arg\max_{h} g\big(\boldsymbol{x}(k),\, h(\boldsymbol{x}(k))\big). \tag{4.3}$$

4.3 FLC Based Local Ramp Metering

4.3.1 Motivations

Optimal freeway local ramp metering has been limited to maintaining maximum mainstream traffic flow by most existing studies. However, freeway local ramp metering also involves traffic on the on-ramp link which should be appropriately treated when developing ramp metering strategies, because the waiting time spent by vehicles on the ramp increases if ramp metering prevents timely merging of these vehicles. This will not only result in unappreciated road priority of these vehicles, but also influence the traffic flow on related surface street links. An ideal way for solving this problem is to take the Total Time Spent (TTS) by vehicles within the whole freeway network as a cost function to measure the efficiency of ramp metering, which is adopted in coordinated freeway ramp metering systems. For freeway local ramp metering, however, there might not be enough detectors on the freeway mainstream link to help calculation of TTS in real freeway systems, because there are only limited detectors on the ramp link and the merging areas of the mainstream link. Given the above consideration, a practical method is to take a weighted total time spent by vehicles within the merging area and on-ramp link as the cost function, which emphasizes a more balanced evaluation of ramp metering efficiency.

Due to the highly nonlinear dynamics of freeway traffic flow behaviors and the randomness in freeway systems, e.g. measurement noise, uncertainty of traffic demand, it is difficult to design a ramp metering algorithm that works the best under various traffic conditions. However, it is possible that the optimal ramp metering strategy be reasonably approximated by control algorithms with parameterized functional approximators, e.g., artificial neural networks and fuzzy logic based control algorithms which have been proven to be universal approximators. FLC based control emulates the reasoning process of human brain which is capable of generalizing the control policies by limited number of fuzzy rules. A desirable feature of FLC is that the control algorithm can approximate any functional mapping if properly designed [82]. Furthermore, FLC based controllers are insensitive to system uncertainties and human expert knowledge can be conveniently incorporated in the controller design process.

Although randomness exists in freeway systems, especially in the traffic demand, the overall traffic conditions are repeated at a macroscopic level. For instance, the traffic demand during the peak hour period is a random value, yet these values are around an average level. The efficiency of the ramp metering algorithm should be evaluated based on the average performance of multiple random trials rather than a single random trial.

Motivated by the above considerations, we propose the FLC based ramp metering algorithm to achieve the performance. The FLC controller is optimally tuned based on

PSO algorithm and freeway traffic simulations.

4.3.2 Design of FLC Algorithm

The characteristics of the above FLC controller depend on both the input fuzzy sets and the parameters in the equations of the consequent part. Due to the adoption of predefined input fuzzy sets, the FLC algorithm is then characterized solely by parameters of the consequent part. Mainstream density (ρ), speed (v) and the on-ramp queue volume (ω) are used as input variables for the ramp metering algorithm. These variables can be measured by deploying loop detectors on the freeway mainstream and on-ramp link. 2 fuzzy labels are defined for each input variable with triangular type fuzzy sets, which was suggested to start with in FLC design [83]. The input fuzzy sets, with input variables normalized into the range of -1 and 1, and the corresponding fuzzy labels are shown in Fig. 4.2. Two fuzzy sets are defined for each variable and are labeled by linguistic variables *LOW* and *HIGH* respectively.

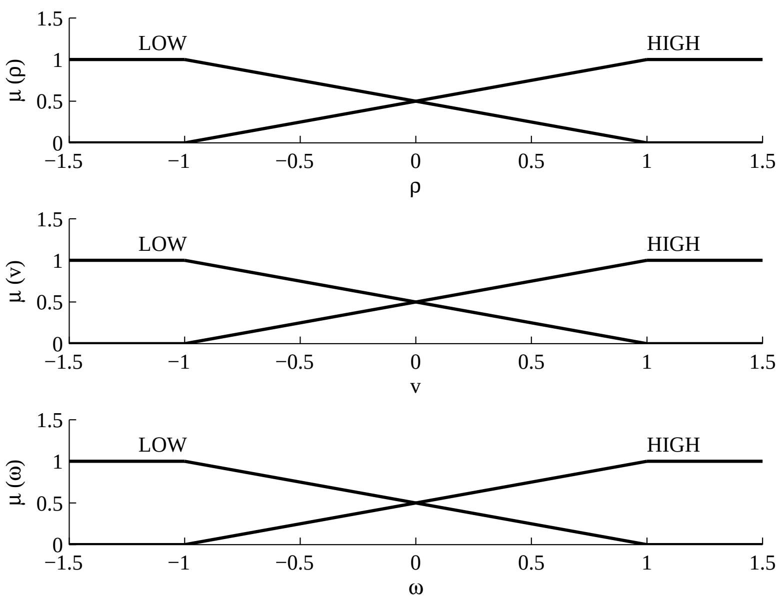


Fig. 4.2: Input fuzzy sets and fuzzy labels.

A similar ramp metering strategy like ALINEA is used here where a desired mainstream density, ρ_d, is to be tracked and the ramp metering signal is determined as follows:

$$r(k+1) = r(k) + \beta(\rho_d - \rho(k)) \tag{4.4}$$

where β is a constant feedback gain. Different from ALINEA, ρ_d is determined by the FLC based algorithm according to realtime traffic conditions. The desired mainstream density is not directly determined by the output of the FLC controller, but treated as the product of a predefined value, ρ_r, and a coefficient, c_ρ, which is determined by the controller instead. An example of the fuzzy rule is:

IF ρ is *HIGH AND* v is *HIGH AND* ω is *HIGH*, *THEN* $c_\rho^l = \theta_0^l + \theta_1^l\rho + \theta_2^l v + \theta_3^l\omega$

where θ_j^l, $j = 0, 1, 2, 3$, are the output parameters of the lth fuzzy rule. The desired mainstream density is eventually calculated as follows:

$$\rho_d = \rho_r \frac{\sum_l \mu^l c_\rho^l}{\sum_l \mu^l}. \tag{4.5}$$

Denote $\boldsymbol{\theta}$ the vector of FLC output parameters, i.e.,

$$\boldsymbol{\theta} = [\theta_0^1, \cdots, \theta_3^1 \ \cdots \ \theta_0^L, \cdots, \theta_3^L] \tag{4.6}$$

where L is the number of rules.

Due to the setting of input fuzzy sets, there are 8 possible combinations of antecedent fuzzy labels as listed in Tab. 4.1. Some of the rules are unrealistic, because the dynamics characteristics of traffic flow determine that when mainstream density is high, the mainstream speed must be low. Fuzzy rules corresponding to combinations of 1, 2, 7 and 8 are unrealistic, therefore, they are removed from the rule base. Due to the settings of input fuzzy sets and rule base, there are 4 fuzzy rules and $4 \times 4 = 16$ tunable parameters.

Finally, the optimal freeway local ramp metering problem is equivalent to seeking the optimal parameter vector, $\boldsymbol{\theta}^*$, such that the cost function is minimized.

Tab. 4.1: Possible combinations of antecedent fuzzy labels in fuzzy rules.

l	$L^l(\rho)$	$L^l(v)$	$L^l(\omega)$
1	*LOW*	*LOW*	*LOW*
2	*LOW*	*LOW*	*HIGH*
3	*LOW*	*HIGH*	*LOW*
4	*LOW*	*HIGH*	*HIGH*
5	*HIGH*	*LOW*	*LOW*
6	*HIGH*	*LOW*	*HIGH*
7	*HIGH*	*HIGH*	*LOW*
8	*HIGH*	*HIGH*	*HIGH*

4.3.3 PSO Based Parameter Tuning

We apply the PSO algorithm for tuning the parameters of the FLC controller. PSO solves an optimization problem by keeping a population of particles in the search space, and each particle is associated with a set of parameters. The parameters of these particles are updated according to simple mathematical formulae. The standard PSO algorithm is expressed by (4.7)-(4.9).

$$V_i^{j+1} = \eta^j V_i^j + c_1 rand()(\boldsymbol{\theta}_i^p - \boldsymbol{\theta}_i^j) + c_2 rand()(\boldsymbol{\theta}_i^g - \boldsymbol{\theta}_i^j) \tag{4.7}$$

$$\eta^j = \eta_{\max} - \frac{(\eta_{\max} - \eta_{\min}) \times j}{Gen} \tag{4.8}$$

$$\boldsymbol{\theta}_i^{j+1} = \boldsymbol{\theta}_i^j + V_i^{j+1} \tag{4.9}$$

During the optimization process, each particle keeps a record of the parameters it has reached with the best performance, this parameter is called the personal best solution. Meanwhile, a neighborhood of 3 particles is defined for each particle, and the parameters with best performance ever reached by particles within the neighborhood are also recorded, which is called the global best solution. The velocity of particles is the vector of parameters' updating signal. The searching and parameter updating mechanism of

PSO can be regarded as a combination of both exploitative and explorative searching behaviors of the particles. The exploitative searching is realized by moving the current solution towards both the personal and global best solutions so as to get closer to the optimum, which might possibly be a local optimum. The explorative searching is realized by retaining the current direction of movement so that broader region in the search space can be explored. As the parameter updating process evolves, the weighting factor η^j decreases so that particles converge towards the optimal solutions. Analysis on convergence properties of PSO was studied by researchers [84–86]. Although the assumption of infinite numbers of generation is practically unsatisfied, PSO algorithms can find good solutions given appropriate selection of parameters in practice.

The configuration parameters of the PSO algorithm are given in Table. 4.2. It should be noted that the values of η, c_1 and c_2 are important to performance of PSO algorithm. Suggested values of these parameters were given in several studies which were considered adequate for some of the usual benchmark problems [84, 87].

Tab. 4.2: Configuration of PSO Algorithm.

Parameters	Value
Swarm Size	20
Gen	100
$\eta_{\max}$	0.9
$\eta_{\min}$	0.4
c_1	2.0
c_2	2.0

Tab. 4.3: Summary of simulation parameters.

ρ_r	a_0	a_1	a_2	ω_{max}
45	0.1	400	0.01	50

4.3.4 Fitness Function

The following cost function is adopted to evaluate the efficiency of the ramp metering controller:

$$\begin{aligned} J = T \sum_{1 \leq k \leq T} \Big\{ & \rho(k) L_n \delta_n + a_0 \omega(k) + a_1 (c_\rho(k) - c_\rho(k-1))^2 \\ & + a_2 \max \left[(\omega(k) - \omega_{max}), 0 \right]^2 \Big\} \end{aligned} \tag{4.10}$$

where L_n is the length of the nth section, δ_n is the number of lanes of section n, a_0, a_1 and a_2 are constant weighting coefficients, T is the length of controller time step, and ω_{max} is the maximum number of vehicles allowable on the on-ramp link. These parameters are summarized in Tab. 4.3, where 45 is the estimated critical density value and queue length over 50 is considered overlong and are penalized more. The values of a_0, a_1 and a_2 are found to be suitable in simulation studies.

Note that (4.10) is a weighted total time spent (WTTS) by vehicles in the merging process which is comprised of four terms. The first term is the time spent by vehicles on the mainstream merging area. The second term is the time spent by vehicles on the on-ramp link. The last two terms are weighted penalties on violent variations in the desired mainstream density signals and overlong queues on the on-ramp link. A cost function in the form of (4.10) represents a more comprehensive assessment of the traffic conditions under ramp metering, taking into consideration of traffic conditions on not only the mainstream link, but also the on-ramp link. The penalty terms on temporal difference in ramp flow rate is out of the practical concern that violent changes of ramp flow rate should be avoided, because real traffic flow changes with a limited rate.

To obtain minimum cost function value from (4.10), the first two terms are the main factors to be considered which are conflicting to each other. To reduce the time spent by vehicles on the mainstream link requires higher traffic flow and speed there, however, to ensure better mainstream traffic flow would prevent on-ramp vehicles from merging which inevitably increase the waiting time spent by vehicles on the on-ramp link. Vice versa, a similar situation would occur, therefore, a balance between the these main aspects is essentially required so as to achieve optimal performance of ramp metering.

4.4 Numerical Experiments

4.4.1 Simulation Setup

To evaluate the proposed approach for freeway local ramp metering, a benchmark freeway system shown in Fig. 4.3 is considered. A 3-lane mainstream link is comprised of 9 mainstream sections of 500 meters, $S1$ to $S9$. An on-ramp link is connected to $S5$ at the beginning location. Three areas, A, B and C, are defined at the mainstream and on-ramp link origins and the mainstream ending location.

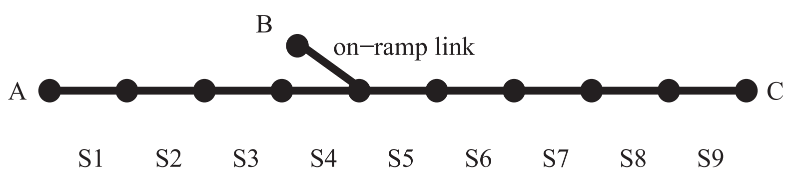


Fig. 4.3: Benchmark PARAMICS freeway model.

The PARAMICS simulation platform is used for modeling the benchmark freeway system. Traffic demands at the mainstream origin and on-ramp link are given in Fig. 4.4.

3 hours' simulation time is considered. The total traffic volumes to be released from origin areas A and B to destination area C are 18000 and 2650 respectively. 10 simulation periods are defined, each of 18 minutes. The fractions of traffic volume released within each period are given as in the graph where a peak traffic demand is presented.

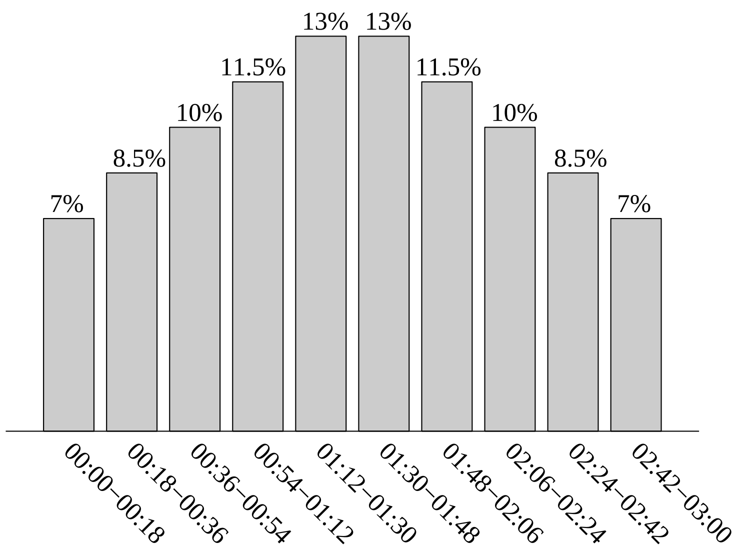


Fig. 4.4: Traffic demand for PARAMICS freeway model.

4.4.2 Results and Discussions

Performance Of PSO

The evolution of average cost function values among all particles in each generation is shown in Fig. 4.5. As shown, the average cost function value has been greatly reduced from an initially large value by roughly 60 percent. This indicates that the controller parameters found by the particles are generally improved towards better performances. Meanwhile, the maximum cost function value among all particles is greatly reduced. The reduced difference between the maximum and average cost function indicates that the parameters found by particles eventually become stable and the corresponding cost functions achieved almost comparable values. During the simulation, the minimum cost function value has not changed much. This is probably because good parameters are found by particles in the initialization stage and these parameters has been kept without much variations throughout the optimization process. Note that randomness exists in freeway traffic and multiple simulation trials are conducted so as to obtain an averaged cost function value to better reflect the appropriateness of the corresponding parameters and controllers. Although the evolution of average cost function value is a bit fluctuated, improvement is quite obvious on the average level.

The above results show that the PSO algorithm can effectively tune the parameters of the FLC controller to improve control performance.

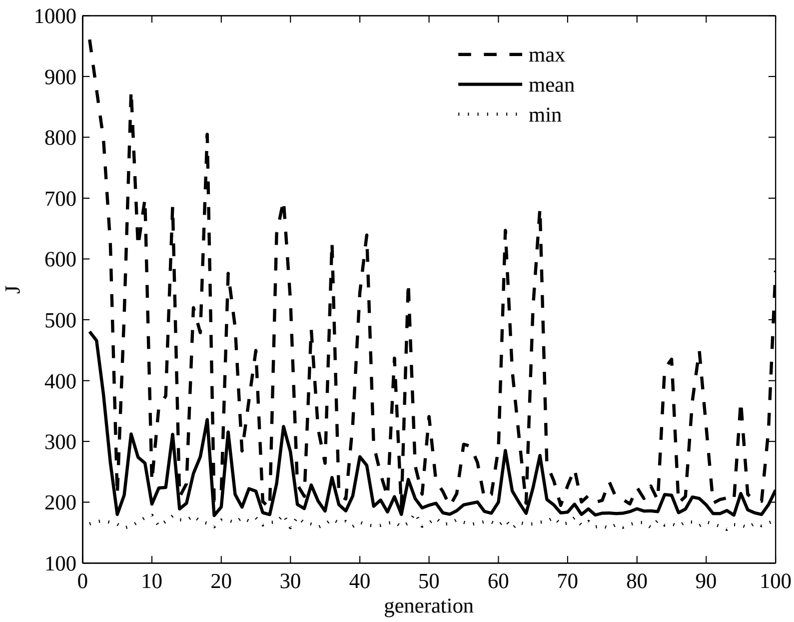


Fig. 4.5: Evolution of cost function.

FLC Based Optimal Ramp Metering

To gain more in-depth look into the FLC based ramp metering, the following additional performance indices are defined to quantitatively evaluate the performances of the parameters in each generation, where i and k denote the indices of the particles and time steps.

ρ^+ the averaged of total mainstream density in each generation calculated as:

$$\rho^+ = \frac{\sum_i \sum_k \rho(k)}{\text{population size}}.$$

q^+ the averaged of total mainstream flow in each generation calculated as:

$$q^+ = \frac{\sum_i \sum_k q(k)}{\text{population size}}.$$

ω^+ the averaged of total queue volume on the on-ramp link in each generation calculated as:

$$\omega^+ = \frac{\sum_i \sum_k \omega(k)}{\text{population size}}.$$

Fig. 4.6 shows the evolution of these indices during the optimization process. As shown, q^+ and ω^+ are generally reduced along the generation axis, while ρ^+ has been increased. It is clear that the improvement in performance of FLC based ramp metering is achieved by allowing more vehicles to be merged into the mainstream such that queueing vehicles on the on-ramp link can be reduced. Meanwhile the mainstream density increases, which results in reduction of mainstream traffic flow.

These results suggest that a tradeoff between mainstream traffic flow and on-ramp queue volume exists on the average level, and optimal ramp metering should keep a proper balance between them. The fine-tuned FLC controllers in the simulations have reduced the total on-ramp queue volume by approximately 50 percent which results in less than 3 percent reduction in average total mainstream traffic flow.

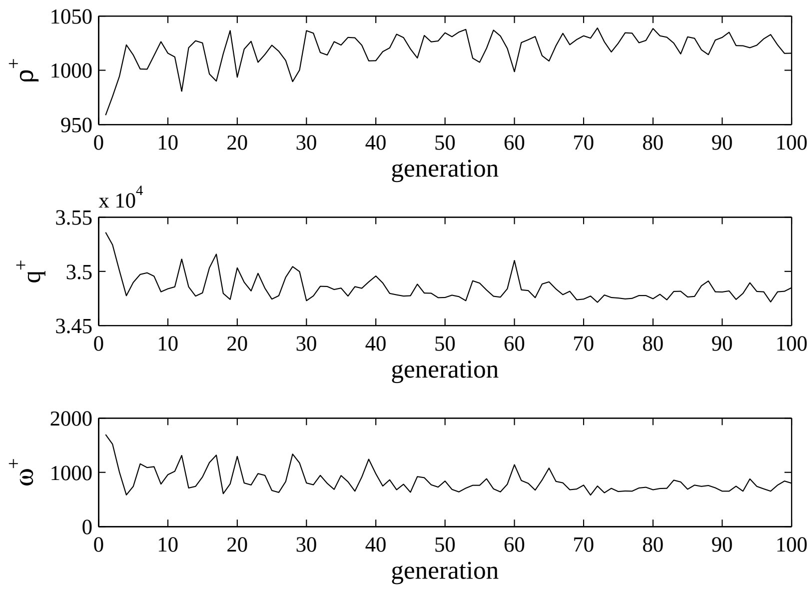


Fig. 4.6: Evolution of additional performance indices.

Further Discussion

In the design of fuzzy rule base, we have removed several unrealistic fuzzy rules from the rule base in the design of FLC controller. The basis for such selection of fuzzy rules is that the characteristics of freeway traffic flow behaviors preclude the occurrence of certain situations described by some fuzzy rules. The average firing weights of the fuzzy rules used in the rule base and those removed from the rule base in the last generation are shown in Fig. 4.7 and Fig. 4.8, where k is the index of simulation time interval in 15 seconds. As shown, average firing weights of fuzzy rules removed from the rule base are insignificant during the whole simulation period. The average firing weights of rule 4 in Tab. 4.1 is considerably insignificant compared with the other three rules in the rule base. This is due to the effect of the fine-tuned FLC controller on ramp metering, which has avoided the situation described by the antecedent part of rule 4, i.e. density is low and speed is high and on-ramp queue volume is high. The fine-tuned ramp metering controller allows vehicles from the on-ramp link to merge freely when mainstream traffic is light, therefore, high queue volume is effectively avoided.

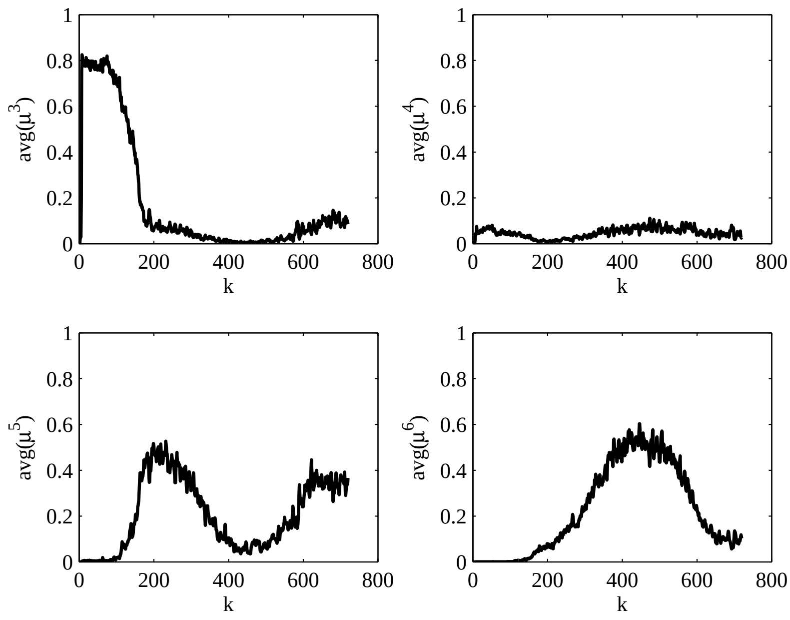


Fig. 4.7: Average weights of fuzzy rules used in the rule base.

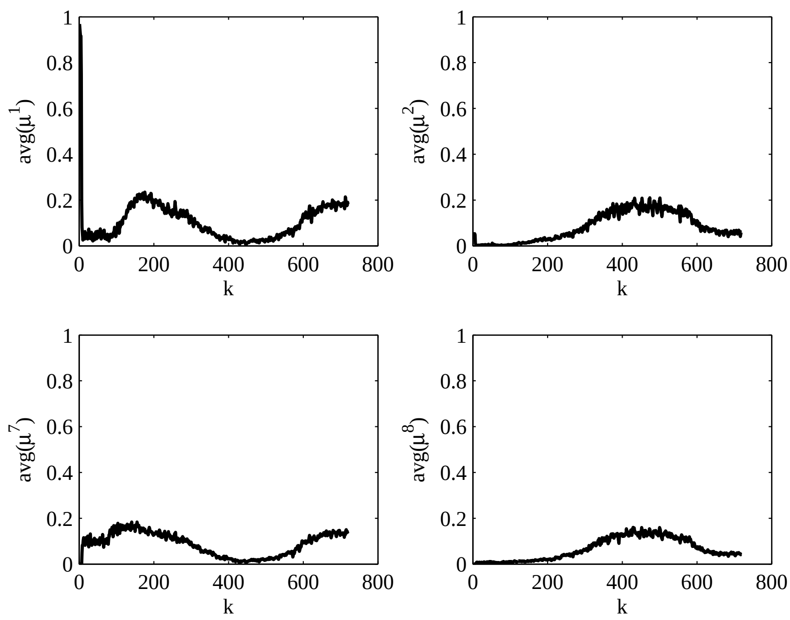


Fig. 4.8: Average weight of fuzzy rules removed from the rule base.

4.5 Conclusion

In this chapter, the optimal freeway local ramp metering problem is solved by using a novel T-S type FLC based ramp metering algorithm. The objective of freeway local ramp metering is to seek a proper balance between traffic on the freeway mainstream and on-ramp link. Input membership functions of the proposed FLC controller are predefined and the size of fuzzy rule base is reduced by incorporating human expert knowledge. Consequent parameters of the FLC controller are fine-tuned using a PSO algorithm and microscopic traffic simulations. Simulation results show that performance of FLC controllers for ramp metering are effectively improved by the proposed parameter tuning scheme, and traffic conditions on the freeway mainstream and on-ramp link are well balanced to provide optimal performance of local ramp metering.

In this chapter, the freeway optimal local ramp metering problem is addressed using an off-line optimization approach. In real freeway traffic systems, the freeway traffic conditions may slowly change after long period of operation due to certain reasons. For example, installation of road pricing infrastructures and alteration of routes at nearby area will affect the drivers' choice of route. Such abrupt changes in the traffic situation will require the controller parameters to be re-tuned so as to ensure optimal system efficiency. Another issue involved with the off-line parameter calibration method is that controller parameters resulted from model based optimization should be further refined so as to achieve the optimal real system performance. The above issues can be address by adaptive parameter tuning, which tunes the controller parameters based realtime system situations. The coming chapter addresses the above problem by proposing an SPSA based adaptive parameter learning method.

Chapter 5

FLC based Adaptive Freeway Local Ramp Metering with SPSA based Parameter Learning

5.1 Introduction

As traffic demand and traffic congestion rate increase in metropolitan areas, the development of freeway infrastructures has greatly increased in the past decades. However, urban streets and expressways traffics are still congested, especially during peak hours. Due to the emergent societal and environmental issues associated with traffic congestion, and the unavailability of land resources, higher efficiency in utilization of existing traffic infrastructures should be pursued instead of blind construction of new ones.

Various freeway traffic control methods have been studied by researchers. Among these methods, ramp metering was reported to be effective in control of freeways and freeway networks. Ramp metering is realized by implementation of a device, usually a traffic light or a two-phase (red and green only) signal together with a signal controller at the on-ramp link. The basis for ramp metering based traffic control is that freeway mainstream traffic is closely related to the on-ramp traffic flow, and freeway traffic conditions around the mainstream merging area can be regulated by regulating the on-ramp merging traffic flow. Ramp metering algorithms can generally be classified into fixed time algorithms and real-time (traffic responsive) algorithms. Fixed time ramp metering have been plagued with low efficiency and sometimes they are counterproductive [28, 78, 79]. This is mainly due to the fact that ramp metering control signals are derived based on historical traffic data and are fixed during specific period of time without considering realtime traffic situations. Traffic responsive ramp metering algorithms determine ramp metering control signals according to realtime traffic conditions. The demand-capacity (DC) algorithm determines the ramp flow based on the difference between a predefined mainstream flow capacity and the measured mainstream flow upstream of the merging area [29]. However, this algorithm adopts a constant mainstream flow capacity, which has been found to be time varying [28].

Many ramp metering algorithms are based on the fundamental diagram of traffic flow, which shows the relationship between mainstream traffic flow and density under homogeneous traffic conditions. As shown in Fig. 1.4, mainstream traffic flow achieves the maximum when density is at the critical value. These algorithms try to maintain the mainstream density at the critical density by ramp metering so as to maximize the mainstream flow. *ALINEA* is a well-known local ramp metering algorithm that is based on the principles of the fundamental diagram [33]. Mainstream occupancy is used instead of density in *ALINEA*, because a proportional relationship between mainstream density and occupancy exists, but occupancy is more convenient to be measured. The occupancy at the downstream location of the merging area is measured and the difference between this occupancy and a reference value, the critical occupancy, is used to correct the ramp metering signal. To address the issue of time-varying critical occupancy in practice, adaptive *ALINEA* that updates the value of critical occupancy is studied in [34]. Studies on freeway traffic control by ramp metering or ramp metering combined with other methods, e.g. route guidance, speed limit control, can be found in [28, 37, 88].

The optimality issue is very important in ramp metering, where the following three important questions should be answered:

1. What is the objective of freeway local ramp metering?

2. What kind of controller structure is suitable for freeway ramp metering?

3. How to validate the efficiency of the ramp metering system?

For the first question, a suitable performance index or cost function is needed for assessing the efficiency of the ramp metering strategies. Most existing studies on freeway local ramp metering aim at pursuing maximum mainstream traffic flow. This strategy is limited by the fact that vehicles on the on-ramp links might be forced to wait if mainstream traffic is congested. In [28], when a predefined limit on the queue length is violated, maximum ramp metering flow is activated to address this issue. However, this strategy aims at avoidance of long on-ramp queues rather than pursuing optimal ramp metering performance for the whole freeway system.

For the second problem, it should be noted that the optimal design of ramp metering controller is challenging due to the highly nonlinear dynamics in freeway traffic flow behaviors and the inherent freeway system randomness, e.g. uncertain traffic demand. For complex systems like freeway systems, it is possible that the optimal ramp metering strategies can be approximated using parameterized functionals, e.g. artificial neural networks. A drawback of these methods is that off-line parameter tuning is required, but the control performance can not be guaranteed with respect system conditions different from that used for parameter tuning. For example, the controller with its parameters tuned under free-flow traffic conditions, will not work effectively under congested traffic conditions. In [89], realtime adaptive fuzzy logic control is oriented, the performance of fuzzy controllers is evaluated based on estimated traffic situations, and hence the ramp metering efficiency relies on the accuracy of traffic demand prediction.

For the third question, traffic simulations are usually adopted to evaluate the efficiency of ramp metering algorithms. Because it is almost impossible to conduct experiments directly on freeway roads, due to the cost issues, safety issues, and the importance of maintaining normal freeway operations. To simulate freeway traffic, both macroscopic and microscopic models can be used. Macroscopic models are comprised of continuous or discrete mathematical equations which show the spatial and temporal relationships between freeway traffic states, e.g., METANET model [5]. Successful application of macroscopic freeway models can be found in [28, 37, 88, 89]. Microscopic models provide detailed descriptions on physical and geometrical properties of vehicles and roads, and the behaviors of vehicles dynamics and their interactions are also well described, e.g., PARAMICS [90]. Microscopic traffic simulation models model the behaviors of Driver-Vehicle Unit (DVU) and the interactions among them. Applications of microscopic traffic simulation models can be found in [17, 46, 91].

From the above analyses, it is clear that research on freeway ramp metering is lacking in the pursuit of optimal overall performance in local ramp metering, which not only emphasizes maintaining good mainstream traffic conditions, but also takes traffic conditions on the on-ramp link into consideration. Meanwhile, realtime control strategies with efficient parameter tuning are needed so as to improve the efficiency of ramp metering under varied traffic situations.

In this chapter, a weighted total time spent ($WTTS$) based cost function is use to assess the efficiency of freeway local ramp metering system. $WTTS$ is defined as a weighted sum of the total time spent by vehicles to pass the mainstream merging area and the total waiting time spent by vehicles on the on-ramp link. By using $WTTS$ as the cost function, traffic conditions on the freeway mainstream and on-ramp link are both taken into consideration. Since fewer detectors are needed for calculation of $WTTS$ compared with that of *TTS*, the implementation cost is reduced. Minimization of $WTTS$ essentially requires that a balance should be properly maintained between traffic on the mainstream and on-ramp link. For example, congested mainstream traffic should be avoided, because it will cost more time to be spent by vehicles to travel through the mainstream merging area, and high on-ramp queue volume should also be avoided, because the time spent by queuing vehicles will increase. A T-S type FLC algorithm is used to make the decisions on the reference mainstream density according to realtime traffic conditions, due to the superiority of FLC in dealing with various uncertainties and the universal approximating capability of *FLC*. To improve the efficiency of the FLC based ramp metering algorithm to achieve the optimal performance, parameters in both the antecedent and consequent parts of FLC are tuned by an SPSA based parameter learning algorithm. The *SPSA* based parameter learning scheme utilizes the macroscopic repetitiveness of freeway traffic to repeatedly make observations on the efficiency of the ramp metering algorithms. Based on these observations, an estimation on gradient information is obtained, which contains information on the relationship between variations of controller parameters and the control performance. The observed performances and estimated gradient, although contaminated with noise, is able to effectively direct the updating of parameters towards better performing directions [67, 74, 75, 92]. The proposed parameter learning scheme possesses several main desirable features. First, the FLC based control algorithm can cope with various traffic conditions due to the rule based control law. Second, system noise is well handled because of the capability of FLC in dealing with system uncertainties and noise. Third, the parameter adaptation mechanism is simple, effective, and suitable for realtime parameter tuning without interrupting normal freeway operations.

The chapter is organized as follows. Section 5.2 provides background knowledge and formulation of the freeway local ramp metering problem. Section 5.3 describes the design of FLC based ramp metering algorithm. Section 5.4 presents the proposed FLC based local ramp metering algorithm and the $SPSA$ based parameter learning algorithm. In Section 5.5, illustrative examples are provided, which demonstrates the efficiency of the proposed method. Section 5.6 concludes the chapter.

5.2 Problem Formulation

5.2.1 Freeway Model

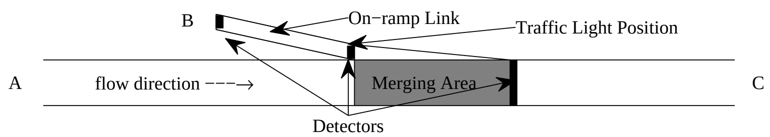


Fig. 5.1: Freeway local ramp metering model.

The freeway local ramp metering system as shown in Fig. 4.1 is considered in this chapter. Detectors are implemented on both the freeway mainstream and on-ram link, where measurement of traffic conditions is obtained. Mainstream average density (or occupancy), speed and queue volume on the on-ramp link can be measured by proper deployment of detectors, i.e. as indicated in Fig. 5.1. The mainstream merging area is the mainstream area connected to the on-ramp link. A detector is located at the downstream location of the mainstream merging area. Mainstream traffic condition can be reflected by the measurement from this detector, i.e. mainstream average flow, average density (which can be equivalently replaced by occupancy in practice) and mean traffic speed. Detectors on the on-ramp link are located at beginning and ending positions so that traffic conditions on the on-ramp link is monitored. Upstream traffic is the mainstream traffic traveling from point A into the merging area, and downstream traffic is the mainstream traffic from the merging area to point C.

5.2.2 Objective

To evaluate the efficiency of freeway local ramp metering, the following $WTTS$ based cost function is used:

$$\begin{aligned} J = T \sum_{1 \le k \le K} \Big\{ & \rho_m(k) L\lambda + w_0 \omega(k) + w_1 (\rho_r(k) - \rho_r(k-1))^2 \\ & + w_2 \max \left[(\omega(k) - \omega_{max}), 0 \right]^2 \Big\} \end{aligned} \tag{5.1}$$

where k denotes the index of time intervals, ρ_m denotes the average traffic density in the merging area, ρ_r denotes the reference mainstream density, ω denotes the queue volume on the on-ramp link, w_0, w_1 and w_2 are constant weighting coefficients, T denotes the length of the time interval, K denotes the total number of time intervals, L denotes the length of the freeway merging area, λ denotes the lane number of the mainstream merging area, and ω_{max} is the maximum number of vehicles allowable on the on-ramp link.

Note that $WTTS$ in (5.1) is comprised of four terms. The first term is the time spent by vehicles on the mainstream merging area. The second term is the time spent by vehicles on the on-ramp link. The last two terms are weighted penalties on violent variations in the desired mainstream density signals and overlong queues on the on-ramp link. A cost function in the form of (5.1) represents a more comprehensive assessment of the traffic conditions under ramp metering, taking into consideration of traffic conditions on not only the mainstream link, but also the on-ramp link. The penalty terms on temporal difference in ramp flow rate is out of the practical concern that violent changes of ramp flow rate should be avoided, because real traffic flow changes with a limited rate. It is similar to TTS except that the total time spent by vehicles on the freeway mainstream in replaced by the total time spent by vehicles in the merging area.

In this chapter, the objective of optimal freeway local ramp metering is to minimize the $WTTS$ value. To obtain minimum cost function value from (5.1), the first two terms are the main factors to be considered which are conflicting to each other. To reduce the time spent by vehicles on the mainstream link requires higher traffic flow and speed there, however, to ensure better mainstream traffic flow would prevent on-ramp vehicles from merging which inevitably increase the waiting time spent by vehicles on the on-ramp link. A similar situation would occur the vice versa. Therefore, a balance between the these main aspects is essentially required so as to achieve optimal performance of ramp metering.

5.3 FLC based Ramp Metering Algorithm

5.3.1 Input Membership Functions

The average traffic density in the mainstream merging area (ρ_m) and the queue volume on the on-ramp link (ω) are used as the input variables of the FLC algorithm. The averaged traffic speed in the mainstream merging area is not used due to the strong correlation between mainstream traffic density and speed, i.e. when average mainstream traffic density is high, the corresponding average mainstream traffic speed is always low, and the vice versa.

Triangular type membership functions are used for input variables. Fig. 6.2 shows the input membership functions when 3 fuzzy labels are used for input variables. The input variables ρ_m and ω are normalized into the range of $[\rho_c - 12,\ \rho_c + 18]$ and $[0,\ \omega_{max}]$ respectively, and the normalized variables are denoted as ρ_m^n and ω^n respectively. Three membership functions are used, which are labelled as *LOW*, *MEDIUM* and *HIGH*. The initial parameters in the input membership functions, i.e. $a_{\rho,0}$, $b_{\rho,0}$, $c_{\rho,0}$, $a_{\omega,0}$, $b_{\omega,0}$ and $c_{\omega,0}$, are as indicated. These variables are treated as tunable parameters which will be adjusted by the parameter learning algorithm. The initial values of these parameters in the input membership functions are also given in Fig. 5.2.

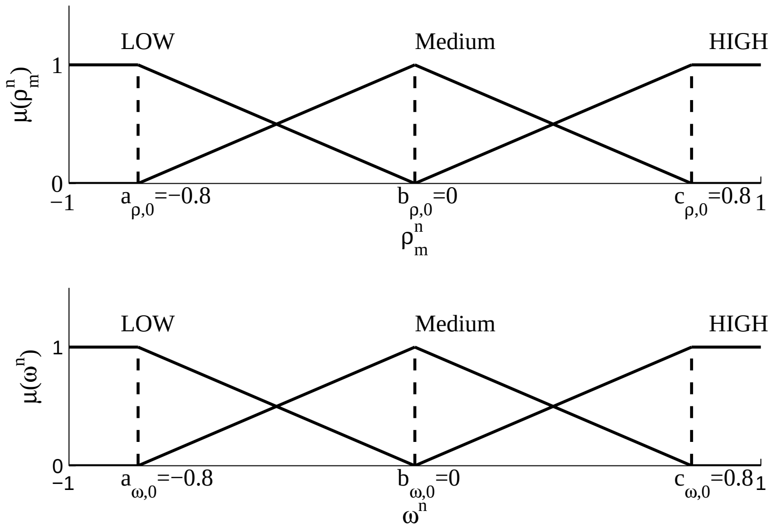


Fig. 5.2: Input membership functions.

5.3.2 Fuzzy Rule Base

Denote $L^l(\rho_m^n)$ and $L^l(\omega^n)$ as the label names of normalized input variables ρ_m^n and ω^n corresponding to the lth fuzzy rule, respectively. Denote $\mu^l(\rho_m^n)$ and $\mu^l(\omega^n)$ as the degree of membership of normalized input variables ρ_m^n and ω^n in their corresponding membership functions of the lth fuzzy rule. An example fuzzy rule is expressed as:

$$IF\ \rho_m^n \text{ is } L^l(\rho_m^n)\ AND\ \omega^n \text{ is } L^l(\omega^n),\ THEN\ \rho_r^l = \theta_0^l + \theta_1^l \rho_m^n + \theta_2^l \omega^n,$$

where θ_j^l, $j \in \{0,\ 1,\ 2\}$ are constant parameters, l denotes the index of the fuzzy rule, and ρ_r^l denotes the output of the lth fuzzy rule, i.e. desired mainstream density. A summary of the fuzzy rule base used is shown in Tab. 5.1.

Tab. 5.1: Fuzzy rule base.

l	$L^l(\rho_m^n)$	$L^l(\omega^n)$	l	$L^l(\rho_m^n)$	$L^l(\omega^n)$
1	*LOW*	*LOW*	6	*MEDIUM*	*HIGH*
2	*LOW*	*MEDIUM*	7	*HIGH*	*LOW*
3	*LOW*	*HIGH*	8	*HIGH*	*MEDIUM*
4	*MEDIUM*	*LOW*	9	*HIGH*	*HIGH*
5	*MEDIUM*	*MEDIUM*			

5.3.3 Inference and Defuzzification

To simplify the *FLC* algorithm, crisp values are used as the output of fuzzy rules instead of equations, because θ_0^l, $l \in [0, N]$ are found to be critical to the performance of *FLC* controller. Denote the firing weight of the lth fuzzy rule as μ^l. It is calculated as:

$$\mu^l = \mu^l(\rho_m^n) * \mu^l(\omega^n). \tag{5.2}$$

The final output, i.e. the desired mainstream density value, denoted as ρ_r is calculated by the following formula:

$$\rho_r = \frac{\sum_{l=1}^{N} \mu^l \rho_r^l}{\sum_{l=1}^{N} \mu^l}, \tag{5.3}$$

where N is the total number of fuzzy rules.

In the first iteration, the consequent parameters of the *FLC* algorithm, i.e. θ_0^l, are randomly generated within the range $[0.8\rho_c,\ \rho_c]$. The consequent parameters initialized this way ensures that performance of freeway local ramp metering is close to the performance of *ALINEA*, which is well established.

Denote $\boldsymbol{\theta}$ as the vector of *FLC* parameters, including both the input membership function parameters and the output parameters. The task of the parameter tuning is to tune $\boldsymbol{\theta}$ such that performance of the local freeway control is optimized, or equivalently, the cost function (J or $WTTS$) is minimized.

5.4 SPSA based Parameter Learning

Denote p as the dimension of tunable parameters $\boldsymbol{\theta}$, i as the index of iterations, and denote $\boldsymbol{\theta}_i$ as the parameters adopted in iteration i. At iteration i, a vector $\boldsymbol{\delta} \in \mathbb{R}^{p\times 1}$ is generated, where each component of $\boldsymbol{\delta}$ is randomly chosen from $+1$ and -1. Two perturbed parameter vectors $\boldsymbol{\theta}_i^+ = \boldsymbol{\theta} + c_i\boldsymbol{\delta}$ and $\boldsymbol{\theta}_i^- = \boldsymbol{\theta} - c_i\boldsymbol{\delta}$ are consecutively used by the *FLC* controller for experimental trials, where c_i is a constant parameter. Denote the resulted performances as J_i^+ and J_i^- respectively. Then an estimation on the gradient $\boldsymbol{g}_i = \frac{\partial J}{\partial \boldsymbol{\theta}}|_{\boldsymbol{\theta}=\boldsymbol{\theta}_i}$ is calculated as:

$$\hat{\boldsymbol{g}}_i = \begin{bmatrix} \frac{J_i^+ - J_i^-}{2c_i\boldsymbol{\delta}[1]} \\ \vdots \\ \frac{J_i^+ - J_i^-}{2c_i\boldsymbol{\delta}[p]} \end{bmatrix}, \tag{5.4}$$

where $\boldsymbol{\delta}_i\,[j]$ denote the jth component of $\boldsymbol{\delta}_i$.

Based on the estimated gradient, system parameters are updated by:

$$\boldsymbol{\theta}_{i+1} = \boldsymbol{\theta}_i - a_i\hat{\boldsymbol{g}}_i \tag{5.5}$$

where a_i is a positive learning gain.

It is worth noting that estimated system gradient $\hat{\boldsymbol{g}}_i$ is contaminated by system noises and disturbances in real systems. A great feature of the *SPSA* based parameter learning algorithm is that parameters can be updated towards directions leading to reduced cost function, even if strong system randomness exists. The convergence of parameters to the global optimal is subject to satisfactions of several assumptions on the considered system and the configurations of algorithmic parameters [67]. The important conditions required on a_i and c_i are as follows:

1. $a_i > 0$, $a_i \to 0$ as $i \to 0$, and $\sum_{i=0}^{\infty} a_i = \infty$

2. $c_i > 0$, $c_i \to 0$ as $i \to 0$, and $\sum_{i=0}^{\infty} (\frac{a_i}{c_i})^2 < \infty$

In this work, a_i and c_i are set as:

$$a_i = \frac{a_0}{(i + A + 1)^{\alpha}} \tag{5.6}$$

$$c_i = \frac{c_0}{(i + A)^{\gamma}}, \tag{5.7}$$

where A, a_0, a_0, α and γ are constant parameters.

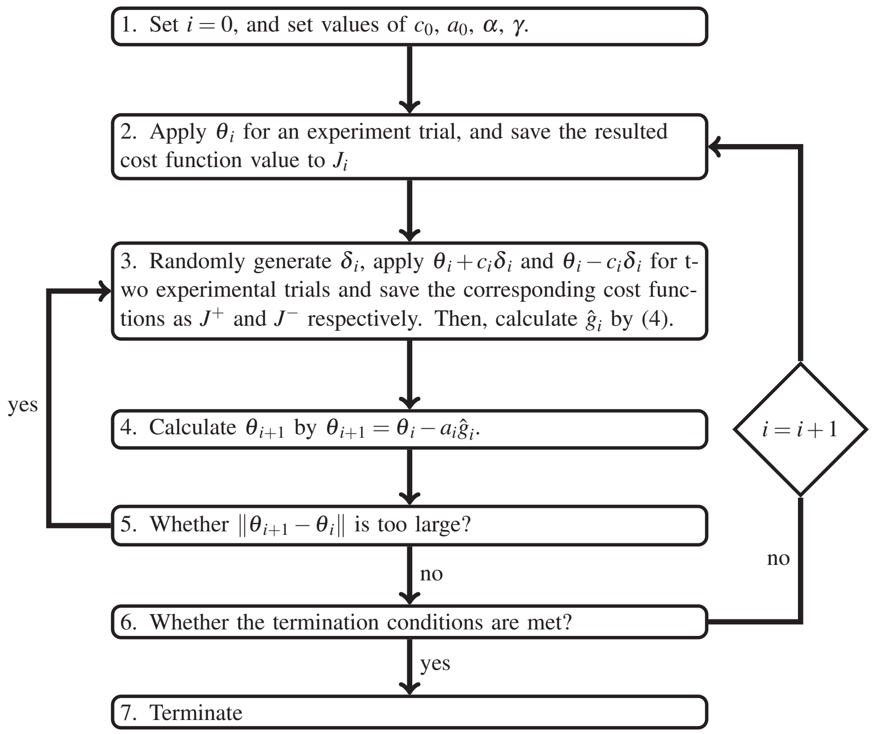


Fig. 5.3: A flow chart of the *SPSA* based parameter learning algorithm.

A flow chart showing the *SPSA* based parameter updating mechanism is summarized in Fig. 5.3. The termination criterion are used to stop further parameter updating when satisfactory performance has been achieved and improvement in the cost function for several consecutive iterations is lower than a predefined value. The parameter learning process is terminated after a predefined number of iterations in this work. To ensure the stability of the parameter updating algorithm, parameter updating is rejected when violent change occurs in the parameters of two consecutive iterations, i.e. $\|\boldsymbol{\theta}_{i+1}-\boldsymbol{\theta}_i\| > \epsilon$, where ϵ is a positive constant.

5.5 Illustrative Examples

5.5.1 Simulation Setup

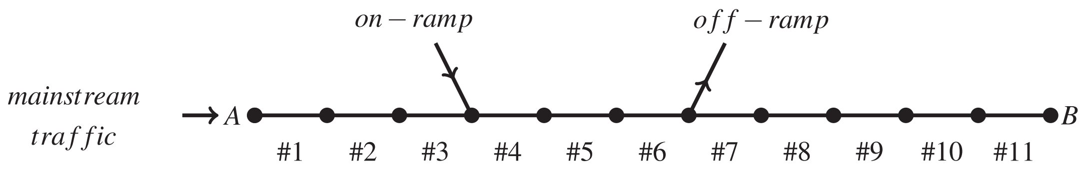


Fig. 5.4: Layout of freeway model. 3-lane freeway mainstream link of 11 mainstream sections is modeled with the METANET model, and single lane on-ramp and off-ramp links are connected to mainstream section 4 and 6 respectively.

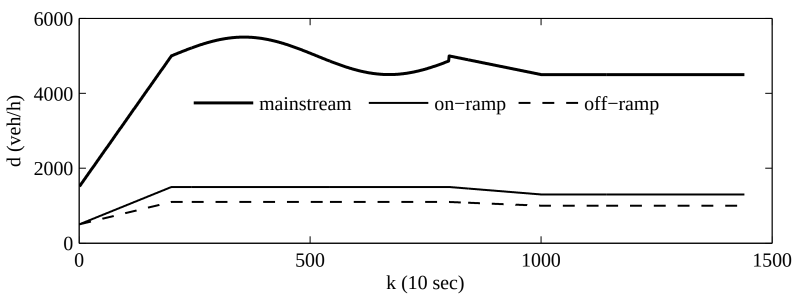


Fig. 5.5: Traffic demand profiles.

To evaluate the proposed approach for freeway local ramp metering, a benchmark freeway system as shown in Fig. 5.4 is considered. The *METANET* freeway traffic flow model is used for modeling the above freeway system, and model parameters in [26] are adopted. Mainstream and on-ramp traffic demand are as shown in Fig. 5.5. A simulation time of 4 hours in total is considered. The traffic demand on the mainstream increases from an initially low flow rate of 1500 veh/h to 5000 veh/h after 200 time intervals. After $k = 200$, mainstream traffic varied around 5000 veh/h with an amplitude of 500 veh/h and finally decreases to 4500 veh/h. Traffic demands at the on-ramp and off-ramp both start from low normal demand flow rates, then increases to their maximum values at $k = 200$. The maximum traffic demands are kept between $k = 200$ to $k = 800$, after $k = 800$, the traffic demands slightly decrease to lower levels. A 10% random noise is imposed on the traffic demand in the simulations.

3 scenarios, *No Control*, *ALINEA* and *FLC*, are investigated in the simulation s-tudies, where no ramp metering, *ALINEA* based ramp metering and *FLC* based ramp metering are used respectively. In *FLC* based ramp metering, *WTTS* and *TTS* based cost functions are both investigated.

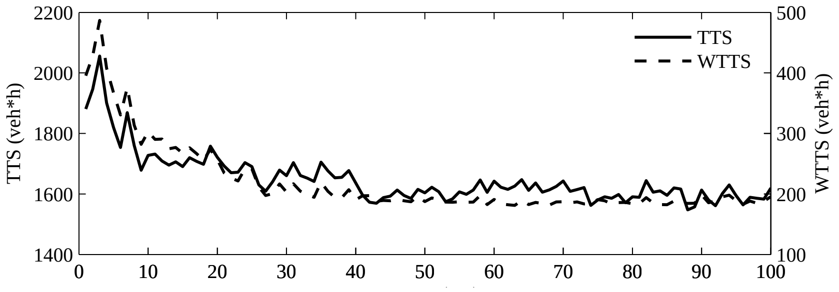
Parameters in the cost function and the *SPSA* tuning algorithm are summarized in Tab. 5.2, where *SPSA* parameters suggested in [75] are adopted.

Tab. 5.2: Summary of simulation parameters.

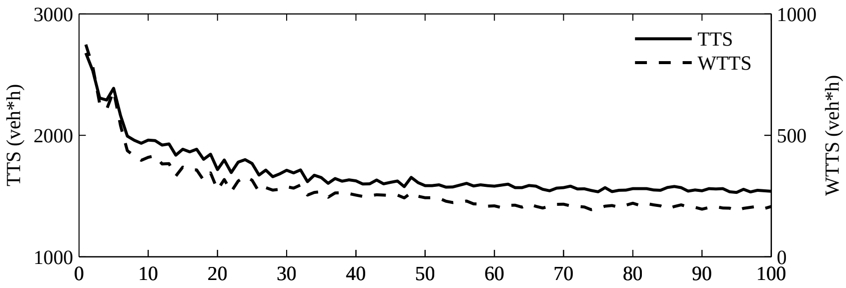
A	a_0	c_0	α	γ	ρ_r	w_0	w_1	w_2	ω_{max}
1	0.25	$0.1\rho_c$	0.602	0.201	33.5	0.01	0.01	0.01	150

5.5.2 Results and Discussion

The evolution of cost functions for 100 iterations are shown in Fig. 5.6. It is clear that, by the *SPSA* based parameter learning, the cost functions are effectively reduced in both cases, and the minimum cost functions are obtained after about 30 iterations. Note that the large values of *WTTS* and *TTS* in the first iteration are due to the randomized initialization of initial parameters. It is also worth noting that there is a sharp initial decline in the cost functions followed by a slow decline in the curves in Fig. 5.6. This is a



(a) Using *WTTS* based cost function.



(b) Using *TTS* based cost function.

Fig. 5.6: Evolution of cost functions.

Tab. 5.3: Summary of cost functions.

Scenario	*WTTS*	*TTS*
No Control	683.9	1923.6
ALINEA	372.7	1764.0
FLC(J=WTTS)	188.3	1585.4
FLC(J=TTS)	207.0	1543.5

typical situation that happens in most optimization problems. Note that the randomly generated perturbation vectors also introduce randomness in the estimated gradient and the corresponding directions of parameter updating. Such randomness is important to avoid convergence to local optimal solutions during the parameter learning process, although some fluctuations are also resulted from this randomness.

The average cost functions (resulted from 20 simulations) associated with the 3 scenarios are summarized in Tab. 5.3. The *TTS* achieved by *ALINEA* based ramp metering is 8.3% lower than that of no control case. The *TTS* obtained in *FLC* based ramp metering is 17.6% and 19.8% lower than that of no control case when *WTTS* and *TTS* based cost functions are used respectively. The proposed *FLC* based method using *WTTS* as cost function achieved a 10% reduction in *TTS* compared with that of *ALINEA*. Meanwhile, *WTTS* are reduced by 45.5%, 72.5% and 69.7% respectively compared with the no control case. The proposed method achieved by the the proposed method is 49.5% lower than that of *ALINEA* based method. It can be seen that the proposed method significantly improves the efficiency of freeway local ramp metering compared with *ALINEA* based method. The performances of *FLC* based ramp metering are very close in cases of *WTTS* and *TTS* based cost functions.

Note that when *WTTS* is used as the cost function, the evolution of *TTS* is similar to that of *WTTS*. A similar situations occurs when *TTS* based cost function is used. These results demonstrate that *WTTS* can replace *TTS* as a performance index to effectively represent the efficiency of freeway local ramp metering system. However, it is important to note that although *WTTS* and *TTS* are shown to be equivalent, *WTTS* based ramp metering has the advantage of requiring fewer detectors, which reduces the implementation cost of freeway local ramp metering system.

The profiles of mainstream density and speed in all scenarios are shown in Fig. 5.7 and Fig. 5.8, the profiles of the on-ramp queue volume are shown in Fig. 5.9. Based on the above results, the following main findings and discussions are concluded:

- The proposed *SPSA* based parameter learning algorithm is effective in tuning the parameters of the *FLC* based ramp metering algorithm and the convergence of cost functions is quite fast, i.e. minimum cost function values are obtained within 30 iterations.

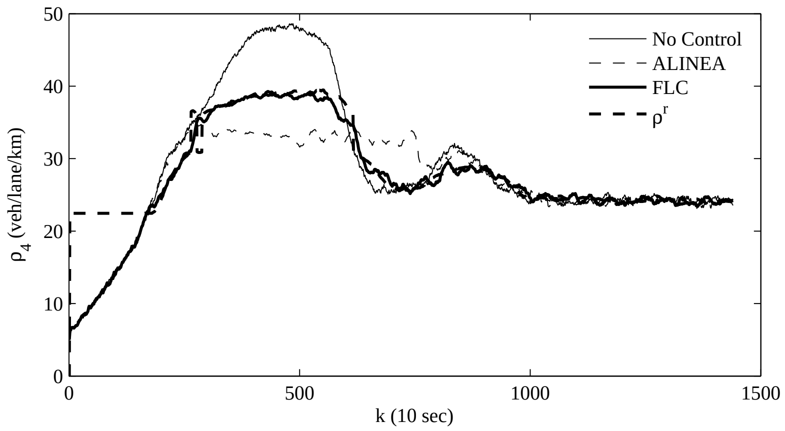


Fig. 5.7: Mainstream density profiles. ρ^r are the reference mainstream density signal, which is generated by the *FLC* algorithm and to be tracked on the mainstream link. *No Control*: Without ramp metering, the mainstream average traffic density increases to about 50 veh/lane/km quickly after the simulation begins, causing the mainstream traffic to be congested. The average mainstream density slowly drops to a lower values after $k = 500$. *ALINEA*: Mainstream average traffic density closely tracks the critical density and congestion is prevented on the mainstream. *FLC*: The mainstream density is increased to about 37 veh/lane/km when traffic demand is high, i.e. during the time $300 < k < 700$ (referred as the congestion period). After this period, mainstream density is reduced.

- *ALINEA* based ramp metering effectively maintains the mainstream density around the critical density and improves the mainstream speed during the congested period in no control case, i.e. the time period when $250 < k < 750$. However, during the congestion period, high queue volume is formed, which is unfair to vehicles on the on-ramp link.

- The *FLC* based ramp metering mitigates the mainstream traffic conditions by adjusting the mainstream traffic density so that the mainstream density will not cause the mainstream speed to drop significantly. Meanwhile, high on-ramp queue volume is avoided. A tradeoff between mainstream traffic and on-ramp traffic is clearly demonstrated. The significantly reductions in the values of TTS and $WTTS$ indicate that a balance between these two traffic conditions has been achieved by the proposed FLC based ramp metering method.

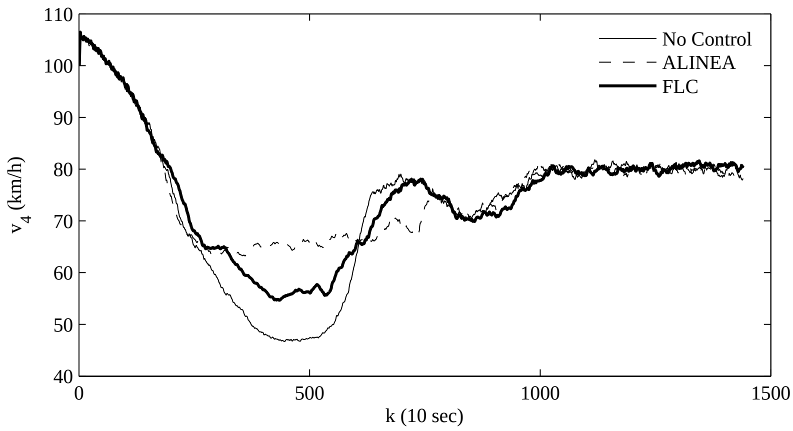


Fig. 5.8: Mainstream speed profiles. *No Control*: Mainstream speed significantly drops to below 50 km/h during the period with high traffic demand. *ALINEA*: Mainstream speed is improved to over 60 km/h during the congestion period. *FLC*: The mainstream speed was kept around a level which is higher than the no control case and lower than the ALINEA case during the congestion period.

5.5.3 Further Discussion

Balance between Mainstream and On-ramp Traffic

It is interesting to note that, by FLC based ramp metering, the controller tends to increase the reference mainstream density value when on-ramp queue increases during the congestion period. Furthermore, the mainstream density is maintained above the critical value during the congestion period. This results in both an increase in the mainstream density and an decrease in the on-ramp queue volume. It is obvious that there has been a balance between traffic conditions on the freeway mainstream and on-ramp link. The optimal FLC based ramp metering maintains the mainstream density

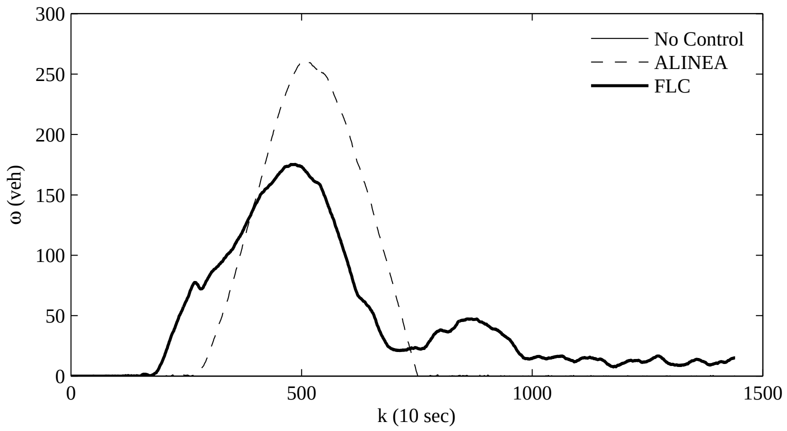


Fig. 5.9: On-ramp queue volume profiles. *No Control*: All vehicles are released into the freeway mainstream and no ramp queue is formed. *ALINEA*: A high queue volume of about 250 vehicles occurs during the congestion period. *FLC*: The on-ramp queue volume is effectively suppressed compared with the *ALINEA* case, i.e. during the congestion period, the maximum queue volume is reduced from 250 vehicles to about 160 vehicles.

higher than the critical density when traffic demand is high so that on-ramp queue volume is reduced. Although the mainstream speed is slightly reduced during the congestion period compared with *ALINEA* case, efficiency of the overall freeway system is improved in termed of reduced values of *TTS* and *WTTS*.

Variations in Traffic Demand

In practice, although traffic demand profiles are repeated at the macroscopic level, variations or disturbances in traffic demand might occur. For instance, the peak traffic demands at certain on-ramp or off-ramp links may occur at an earlier or later times, or randomly occur within a specific time period. It is highly desirable that performance of the ramp metering system is consistent irrespective of these variations. To investigate the performance of the proposed method under these circumstances, additional case studies are conducted to consider varied traffic demand, i.e. the occurrence time of the maximum traffic demand is randomly generated in different simulations. The occurrence time of the maximum traffic demand at the on-ramp and off-ramp link are randomly distributed within a range of 100 time intervals around that of the previously defined traffic demand in Fig. 5.5. Examples of the random demand profiles for the on-ramp and off-ramp link are shown in Fig. 5.10.

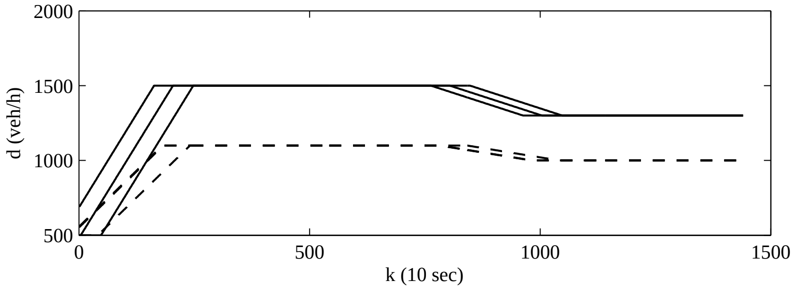


Fig. 5.10: Random traffic demand at the on-ramp and off-ramp links. The demand profiles in solid curves are for the on-ramp link and profiles in dashed curves are for the off-ramp link. A 10% random noise is applied in the simulations.

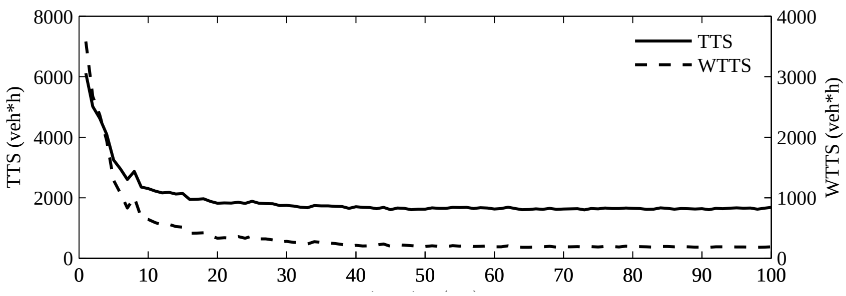


Fig. 5.11: Evolution of TTS and $WTTS$ with random occurrence of maximum traffic demand. Both TTS and $WTTS$ values are significantly reduced. The minimum values are obtained after about 40 iterations.

Using $WTTS$ as the cost function, the evolution of $WTTS$ and TTS values are shown in Fig. 5.11. It is clear that although randomness exists in the occurrence of maximum traffic demand, the proposed method effectively finds the optimal ramp metering policies. The minimum TTS value is consistent with that reported in previously simulations. The results of the additional case studies demonstrate that the proposed method is very efficient in coping with various randomness and uncertainties in freeway traffic system.

Implementation Issues

The TTS values in the initial iterations are quite high, therefore, the FLC algorithms with randomly generated parameters are not suitable for implementation due to its poor performance. After about 40 iterations, the performance of the FLC algorithms is quite good, hence, they can be applied for real implementation with satisfactory performance. Due to the approximation natural of traffic flow models, the further tuning might be necessary after implementation in order to achieve the optimal performance of the real system. The proposed SPSA based parameter learning algorithm can be used for this task, because it can achieve consistent improvement in the system performance, as demonstrated in the case studies. Most importantly, the parameter learning task can be realized without interrupting the normal operation of freeway systems, because parameters are kept unchanged within each round of freeway operation and parameter updating can be carried out after the freeway operation hours, i.e. during midnight time when traffic load is very light and no ramp metering is needed. Above all, the proposed parameter tuning method is quite suitable for realtime implementations.

5.6 Conclusion

The freeway local ramp metering problem is addressed by a proposed FLC based decision making algorithm with SPSA based parameter learning. A T-S type FLC algorithm is designed to determine a reference mainstream density according to realtime traffic conditions, and the reference mainstream density is maintained by $ALINEA$ based ramp metering algorithm. The objective of optimal freeway local ramp metering is to minimize a $WTTS$ based cost function, which requires seeking a balance between mainstream traffic and on-ramp traffic. The parameters of the *FLC* controller are effectively tuned by an *SPSA* based parameter learning algorithm. Simulation studies demonstrate that the proposed method is very efficient in improving the performance of freeway local ramp metering, irrespective of variations and uncertainties in the freeway traffic system. In particular, *TTS* is reduced by over 17.6% compared with no control case, and by over 10% compared with that of *ALINEA* case. *WTTS* is reduced by over 72.5% compared with no control case, and by over 49.5% compared with that of *ALINEA* case. Traffic conditions on the freeway mainstream and on-ramp link are well balanced so that the system wide performance of freeway local ramp metering achieves the optimal. It is also demonstrated that *WTTS* and *TTS* are equivalent performance indices for measuring the performance freeway local ramp metering, but the proposed *WTTS* based ramp metering are less expensive, which makes *WTTS* more suitable for practical implementations.

By Chapter 5, the FLC based freeway local ramp metering has been extensively studied and its potential has been demonstrated by the improved efficiencies of freeway local ramp metering systems. For large freeway networks, the ramp metering problem is more complex due to the complicated coupling among neighboring areas. Direct extension of the FLC based ramp metering to the networked freeway systems is inappropriate. This is because when the number of input variables increase, the number of tunable parameters would increase exponentially, making parameter tuning extremely hard. To avoid the above problem, Chapters 6 and 7 propose a divide-and-conquer based method and a macroscopic scheduling based method respectively. Both methods are simple, efficient and require low implementation cost.

In the coming chapter, the local coordinated ramp metering (LCRM) method is first presented. The LCRM method differs from existing centralized control framework based coordinated ramp metering strategies, which suffer from several drawbacks, e.g. requiring continuous computation with complex model involved, lacking system flexibility and high communication cost. The main innovation by the LCRM strategy is that coordinations are carried out among neighboring controllers rather than among all controllers due to the strong interactions among neighboring controllers. Furthermore, communication cost is reduced by the local coordination strategy and complex freeway model involved computation is not required.

Chapter 6

A Novel and Efficient Local Coordinative Freeway Ramp Metering Strategy with SPSA based Parameter Learning

6.1 Introduction

Freeway traffic management is an important area of modern intelligent transportation systems. Improving the efficiency of freeway traffic management has become an emergent task for administrators of freeway facilities due to the freeway traffic congestions, which cause various environmental and societal problems, e.g. increased air pollution and fuel consumption, and increased travel time. The unavailability of sufficient land resources is another factor that motivates researchers to pursue more efficient use of existing freeway facilities. Freeway ramp metering can effectively relieve or prevent freeway traffic congestions by regulating the merging activities of on-ramp traffic. Ramp metering is realized by implementation of a device together with a signal controller at the on-ramp link.

Ramp metering strategies can be generally classified into two categories: local ramp metering strategy and coordinated ramp metering strategy. Local ramp metering strategies use traffic measurement at the vicinity of the on-ramp link to determine the ramp metering signals. The objective is to keep traffic conditions around the on-ramp link properly maintained, e.g. to maximize the mainstream traffic flow, to prevent congestion. Well-known local ramp metering strategies are the demand-capacity (DC) and occupancy (OCC) strategies [29]. DC and OCC aim at maintaining the mainstream traffic flow at the capacity, and feed-forward disturbance rejection schemes are used based on mainstream measurement of flow and occupancy respectively. It was reported by later works that the flow capacity in the mainstream merging area may substantially vary from day to day under similar environmental conditions [32]. Hence predefined mainstream capacity may lead to inefficient ramp metering [27]. The $ALINEA$ strategy [33] is a well known ramp metering algorithm, which can be used for effective freeway local ramp metering [33]. The basic idea of $ALINEA$ based local ramp metering is that the maximum average mainstream traffic flow (Q_{max}) is obtained when the mainstream average density (or occupancy) is kept around a critical density ρ_c (or critical occupancy), according to the fundamental diagram of freeway traffic as shown in Fig. 1.4. Variants of the $ALINEA$ were also studied [34, 35]. It was also found that critical occupancy, at which mainstream capacity flow occurs, is more stable even under adverse weather conditions [32]. An iterative learning control (ILC) based approach was proposed to maintain mainstream average densities at the critical density under unknown but repeated system disturbance, i.e. exiting traffic flow at off-ramp links [62].

Coordinated ramp metering strategies determine the ramp metering signals based on traffic conditions within the whole freeway network. For coordinated ramp metering problems, the objective is to pursue the optimal efficiency of the freeway traffic system, e.g. to minimize the total time spent (TTS) by vehicles within the freeway system, to minimize the fuel consumption or travel time. Compared with local ramp metering s-trategies, coordinated ramp metering strategies is capable of more efficient freeway ramp metering, when there are multiple bottlenecks on the freeway or limited storage space on the on-ramp links. Coordinated ramp metering algorithms based on multi-variable control [42] and optimal control methods were both investigated [26, 28, 37, 81, 93–96]. The multi-variable control based strategy is limited by the use of linearized traffic flow model, which becomes inefficient under heavy congestion [36]. The optimal control based strategies requires complex numerical solution algorithms, which might cause difficulty in field implementations. Model predictive control (MPC) based methods are also optimal control based strategies, where macroscopic traffic flow model and continuous computa-tional power is required [28, 37, 49] It should be noted that existing coordinated ramp metering algorithms are based on the centralized control framework, which suffers from the difficulties with operation, high maintenance cost and lack of flexibility.

In view of the above situation, it is desirable to have a coordinated ramp metering strategy which is capable of achieved better efficiency than uncoordinated ramp metering strategies, while avoiding the pitfalls of centralized control methods.

In this chapter, a local coordinative ramp metering strategy is proposed in an ef-fort to address the limitations of existing coordinated ramp metering strategies. By the proposed approach, all local ramp metering controllers exchange their measurement in-formation with their neighboring controllers and a local coordination scheme is adopted. The *ALINEA* algorithm is used by local ramp metering controllers to maintain their local mainstream densities at corresponding reference values, which are determined based on both the local traffic measurement and the traffic measurement exchanged from neighboring controllers. Such a information exchange scheme requires communications among neighboring local controllers. Compared with the communication required by centralized control based strategies, under which all controllers have to communicate with the control center, the communication cost can be greatly reduced. This is because no matter where the control center is located in centralized control strategies, there is always a large number of controllers that are located remotely and require higher cost to communicate with the control center. Additionally, the coordinated ramp metering algorithms are only effective when the ramps are closely located [97], which suggests that local coordination activities among neighboring on-ramps are more important than those among on-ramps remotely located. In this chapter, an *FLC* based local coordinative decision making algorithm is proposed to determine the local controllers' reference mainstream density signals based on local and exchanged measurement information. The *FLC* based algorithm can effectively deal with the uncertainties and noises in freeway system, and the rule based control structure is simple and easy to understand. Since there is no reliable a priori expert knowledge for the freeway system, the local coordinative decision making algorithm is tuned by a simple and efficient *SPSA* based parameter learning algorithm to find the optimal parameters in the *FLC* algorithm. Using the *SPSA* based parameter learning scheme, the local coordinative decision making algorithms can be effectively adjusted to improve the efficiency of coordinated ramp metering system.. Furthermore, the *SPSA* based parameter learning can be carried out without interrupting the routine operation of freeway networks, which makes it suitable for real implementations. Additionally, no realtime model involvement is required by the proposed strategy, which has a model-free nature; and the feedback control based *ALINEA* algorithm makes the propose strategy insensitive to unexpected disturbances. The proposed coordinated ramp metering strategy can be realized by implementing communication devices in uncoordinated local controllers, and the structure of the control system can be easily modified to adapt to changes in the freeway network structure.

6.2 Problem Formulation

6.2.1 The Problem

Consider a freeway system comprised of multiple freeway mainstream links, which are divided into N sections. Denote n as the index of mainstream sections and L_n as the length of section n. Denote the λ as the index of on-ramp links, O as the total number of on-ramp links.

The local coordinative decision making algorithm for on-ramp λ can be viewed as a mapping f_λ from its input, i.e. $\boldsymbol{x}(k)$, comprised of local and exchanged traffic measurement, to the output, i.e. $y = \rho^r_\lambda(k)$, the reference mainstream density at on-ramp λ. This mapping can be expressed as:

$$\rho_{r,\lambda}(k) = f_\lambda(\boldsymbol{x}(k)). \tag{6.1}$$

$\rho_{r,\lambda}$ is used as the desired mainstream density by the *ALINEA* based ramp metering algorithm instead of the critical density. Hence the ramp metering flow rate at on-ramp λ is determined as:

$$r_\lambda(k+1) = r_\lambda(k+1) + \beta(\rho_{r,\lambda}(k) - \rho_\lambda(k)), \tag{6.2}$$

where r_λ and ρ_λ are the ramp flow rate and average mainstream density at on-ramp λ.

Let J denote the cost function that measures the efficiency of the freeway ramp metering system. In this chapter, *TTS* based cost function is used, which is calculated as:

$$J = T\sum_{k=1}^{T}\left\{\sum_{n=1}^{N} L_n\sigma_n\rho_n(k) + \sum_{\lambda=1}^{O}\left[\omega_\lambda(k) + a_r(r_\lambda(k) - r_\lambda(k-1))^2 + a_\omega(max\{\omega_\lambda(k) - \omega_{max}, 0\})^2\right]\right\}, \tag{6.3}$$

where ω_λ denotes the queue volume at on-ramp λ, σ_n denotes the number of lanes on the mainstream section n, a_r and a_ω are two weighting parameters. ω_{max} denotes a predefined maximum limit on the on-ramp queue volume, and queue volume higher than this level will be penalized.

Note that there are 4 terms on the right hand size of (6.3). The first term is the total time spent by vehicles on the freeway mainstream. The second term measures the total waiting time spent by vehicles on the on-ramp links. The third and fourth terms penalizes violent changes in the on-ramp flow rates and queue volumes exceeding the maximum limit. Note also that different values of ω_{max} and a_ω indicate varied emphasis on the on-ramp queue volumes, i.e. smaller a_ω and larger ω_{max} indicate that lower emphasis is given to constrain the on-ramp queue volume and higher queue volumes are allowable, and the vice versa. The parameters in the cost functions used here are given in Tab. 6.1.

Tab. 6.1: Parameters in the cost function.

a_r (h^3/veh^2)	a_ω (h/veh^2)	ω_{max} (veh)
0.01	0.01	250

6.2.2 Objective

$\rho_{r,\lambda}$ in (6.1) can be rewritten as a function of $\boldsymbol{\theta}$ as well, namely

$$\rho_{r,\lambda} = f(\boldsymbol{x}, \boldsymbol{\theta}). \tag{6.4}$$

The objective of the local coordinative ramp metering strategy is to adaptively adjust the reference mainstream density signals for all on-ramp links, $\rho_{r,\lambda}$, $\lambda \in [1, O]$, according to realtime traffic conditions such that J is minimized.

6.3 The Local Coordinative Ramp Metering Strategy

6.3.1 System Structure

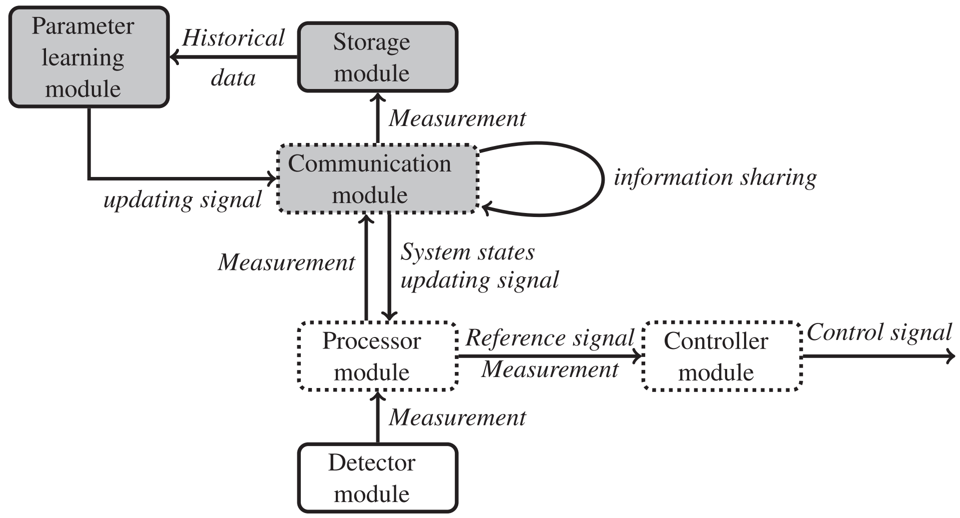


Fig. 6.1: The diagram of the cooperative coordination system.

The structure of the cooperative coordination system is shown in Fig. 6.1. Main components in the diagram are described as follows:

Detector module This module is comprised of loop detectors buried on the freeway mainstream and ramp links, which measures the traffic states on the freeway mainstream and on-ramp links. The measurement information is supplied to the communication module and processor module.

Communication module This module includes the data transmitter and receiver devices. Local measurement information obtained at neighboring on-ramp links is internally exchanged through measurement sharing using the communication module.

Processor module The processor module is comprised of a computing unit, which determines the control signal based on the available system information, and supply the control signal to the controller. Updating signals for parameters of the ramp metering algorithms are received from the communication module to adjust the local ramp metering algorithm.

Controller module The controller module includes the traffic signal light system, which regulates the ramp metering rates at the on-ramp entry.

Storage module The storage module collects and stores measurement information from communication modules of local control systems, and these measurement data is supplied to the parameter learning module.

Parameter learning module The parameter learning module takes historical data as its input, and determines the updating signals for the parameters of the processor module in order to improve the system performance.

Note that in Fig. 6.1, three layers can be identified in the hierarchy of the local coordinative ramp metering system. The first layer is the local ramp metering control layer, which includes the detector module, processor module and controller module. The second layer is the communication layer, containing the communication module. The third layer is the centralized control layer comprised of the parameter learning module and the data storage module. The three-layer hierarchy is typical in centralized control systems. The third layers is at the top of the hierarchy which determines the macroscopic level behaviors of the ramp metering system, i.e., adjusting the behaviors of all local controllers by tuning the parameters of the local ramp metering algorithms. The second layer is an intermediate layer, which connects the first and third layer. Note also that there is no explicit physical boundary between this layer and the other two layers, because communication modules exist in both the local control devices and the control center. The first layer is the basic layer, where ramp metering control signals are generated and applied.

The structure of the proposed local coordinative ramp metering strategy differs from that of traditional centralized control systems, where major differences are summarized as follow:

1. The processor module takes both locally measurement and measurement exchanged from neighboring controllers as its input, while in traditional centralized control systems, only locally measurement is used.

2. Data exchange among local controllers is implemented in the proposed strategy, while in existing centralized control systems, for example, *MPC* based control systems, communication is only implemented between the control center and local controllers.

3. By the proposed strategy, updating signals are used to update parameters of the coordinative decision making algorithms instead of directly updating the local reference signals.

Note that the communication module in Fig. 6.1 is important for the proposed strategy, because it does not require communication between the local controller and the control center in realtime. Once the parameters of the coordinative decision making algorithms are determined, communication within limited distance among neighboring controllers is needed, reducing the communication cost at run time.

6.3.2 Input Membership Functions

Without loss of generality, a local coordinated ramp metering system containing two local controllers are considered for controller design as well as the illustrative examples presented in the next section. The controller design method can be easily extended for more generic cases.

Let the two local controllers indexed as 1 and 2 respectively. The average mainstream traffic densities, i.e. ρ_1 and ρ_2, and the queue volumes on the on-ramp links, i.e. ω_1 and ω_2, are used as the input variables of the *FLC* based coordinative decision making algorithm. The averaged traffic speed in the mainstream merging area is not used due to the strong correlation between mainstream traffic density and speed, i.e. when average mainstream traffic density is high, the corresponding average mainstream traffic speed is always low, and the vice versa.

Triangular type membership functions are used for input variables. Fig. 6.2 shows the input membership functions with 2 fuzzy labels for mainstream average density and on-ramp queue volume. The average densities of both controllers are normalized into the range of [25, 45], and on-ramp queue volumes of both controllers are normalized into the range of $[0,\ \omega_{max}]$. The normalized variables are denoted as ρ_1^n, ρ_2^n, ω_1^n, and ω_2^n respectively. The two fuzzy labels are labelled as *LOW* and *HIGH* for each variable. The initial parameters in the input membership functions, i.e. $a_{\rho,1}$, $b_{\rho,1}$, $a_{\rho,2}$, $b_{\rho,2}$, $a_{\omega,1}$, $b_{\omega,1}$, $a_{\omega,2}$, and $b_{\omega,2}$ are as indicated. These variables are treated as tunable parameters which will be adjusted by the parameter learning algorithm. The initial values of these parameters in the input membership functions are also given in Fig. 6.2.

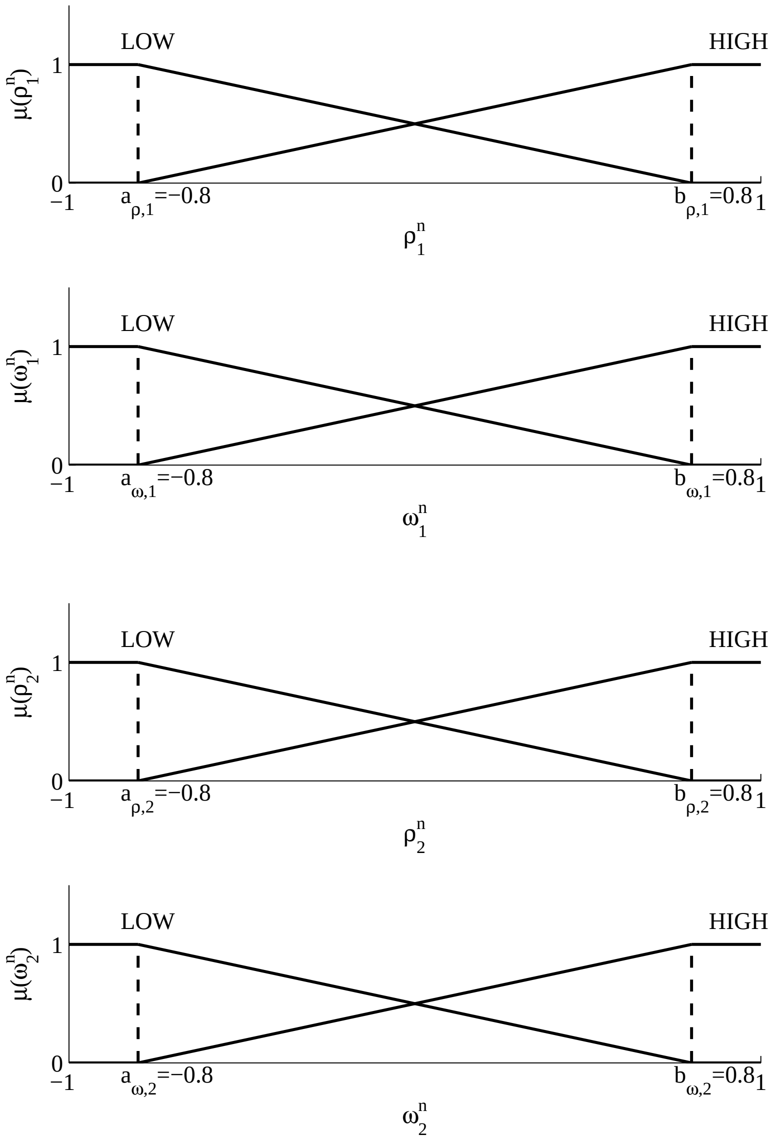


Fig. 6.2: Input membership functions.

6.3.3 Fuzzy Rule Base

Denote $L^l(\rho_1^n)$, $L^l(\rho_2^n)$, $L^l(\omega_1^n)$ and $L^l(\omega_2^n)$ as the label names of normalized input variables ρ_1^n, ρ_2^n, ω_1^n, and ω_2^n corresponding to the fuzzy rule indexed by l. Denote $\mu^l(x)$ as the degree of membership of normalized input variables x in their corresponding membership functions of the lth fuzzy rule. An example fuzzy rule is expressed as:

6.1
$$\begin{gathered} \mathit{IF}\ \rho_1^n \text{ is } L^l(\rho_1^n)\ \mathit{AND}\ \rho_2^n \text{ is } L^l(\rho_2^n)\ \mathit{AND}\ \omega_1^n \text{ is } L^l(\omega_1^n)\ \mathit{AND}\ \omega_2^n \text{ is } L^l(\omega_2^n), \\ \mathit{THEN}\ \rho_r^l = \theta_0^l + \theta_1^l\rho_1^n + \theta_2^l\rho_2^n + \theta_3^l\omega_1^n + \theta_4^l\omega_2^n, \end{gathered} \tag{6.5}$$

where θ_j^l, $j \in \{0, 1, 2, 3, 4\}$ are constant parameters, l denotes the index of the fuzzy rule, and ρ_r^l denotes the output of the lth fuzzy rule, i.e. desired mainstream density. A summary of the fuzzy rule base used is shown in Tab. 6.2.

Tab. 6.2: Fuzzy rule base.

l	Input Fuzzy Label				l	Input Fuzzy Label			
	$L^l(\rho_1^n)$	$L^l(\rho_2^n)$	$L^l(\omega_2^n)$	$L^l(\omega_2^n)$		$L^l(\rho_1^n)$	$L^l(\rho_2^n)$	$L^l(\omega_2^n)$	$L^l(\omega_2^n)$
1	*LOW*	*LOW*	*LOW*	*LOW*	9	*HIGH*	*LOW*	*LOW*	*LOW*
2	*LOW*	*LOW*	*LOW*	*HIGH*	10	*HIGH*	*LOW*	*LOW*	*HIGH*
3	*LOW*	*LOW*	*HIGH*	*LOW*	11	*HIGH*	*LOW*	*HIGH*	*LOW*
4	*LOW*	*LOW*	*HIGH*	*HIGH*	12	*HIGH*	*LOW*	*HIGH*	*HIGH*
5	*LOW*	*HIGH*	*LOW*	*LOW*	13	*HIGH*	*HIGH*	*LOW*	*LOW*
6	*LOW*	*HIGH*	*LOW*	*HIGH*	14	*HIGH*	*HIGH*	*LOW*	*HIGH*
7	*LOW*	*HIGH*	*HIGH*	*LOW*	15	*HIGH*	*HIGH*	*HIGH*	*LOW*
8	*LOW*	*HIGH*	*HIGH*	*HIGH*	16	*HIGH*	*HIGH*	*HIGH*	*HIGH*

6.3.4 Inference and Defuzzification

To simplify the *FLC* algorithm and mitigate the computational burden, crisp values are used as the output of fuzzy rules instead of equations, because θ_0^l, $l \in [0, N]$ are found to be critical to the performance of *FLC* controller. Denote the firing weight of the lth fuzzy rule as μ^l. It is calculated as:

$$\mu^l = \mu^l(\rho_1^n) * \mu^l(\rho_2^n) * \mu^l(\omega_1^n) * \mu^l(\omega_2^n). \tag{6.6}$$

The final output, i.e. the reference mainstream density value, denoted as ρ_r is calculated by the following formula:

$$\rho_r = \frac{\sum_{l=1}^{N} \mu^l \rho_r^l}{\sum_{l=1}^{N} \mu^l}, \tag{6.7}$$

where N is the total number of fuzzy rules. For each on-ramp controller λ, a separate *FLC* algorithm is used, and the resulted ρ_r in (6.7) is used as the reference mainstream density $\rho_{r,\lambda}$ in (6.1).

In the first iteration, the consequent parameters of the *FLC* algorithm, i.e. θ_0^l, are set equal to ρ_c. Since the reference mainstream density is equal to the critical density in the first iteration, the performance of the ramp metering system in the initial iteration is identical to that of *ALINEA*, which is well established.

6.3.5 Objective

Note that the coordinative decision making algorithm can be different at different locations, therefore, separate decision making algorithms are needed for each local controller. Denote $\boldsymbol{\theta}$ as the vector of all *FLC* parameters, including both the input membership function parameters and the output parameters.

Then, the objective of the parameter learning task is to tune $\boldsymbol{\theta}$ such that performance of the local freeway control is optimized, or equivalently, the cost function (J or TTS) is minimized.

6.3.6 SPSA Based Parameter Learning

Denote p as the dimension of $\boldsymbol{\theta}$, i as the index of iterations, and denote $\boldsymbol{\theta}_i$ as the parameters adopted in iteration i. At iteration i, a vector $\boldsymbol{\delta}_i \in \mathbb{R}^{p\times 1}$ is generated, where each component of $\boldsymbol{\delta}_i$ is randomly chosen from $+1$ and -1. Two perturbed parameter vectors $\boldsymbol{\theta}_{i+} = \boldsymbol{\theta}_i + c_i\boldsymbol{\delta}_i$ and $\boldsymbol{\theta}_{i-} = \boldsymbol{\theta}_i - c_i\boldsymbol{\delta}_i$ are used by the local coordinative ramp metering strategy for two experimental trials, where c_i is a constant parameter. Denote J_{i+} and J_{i-} as the corresponding cost function resulted from these two experiments. An estimation on the gradient, i.e. $\boldsymbol{g}_i = \frac{\partial J}{\partial \boldsymbol{\theta}}|_{\boldsymbol{\theta}=\boldsymbol{\theta}_i}$, is then calculated as:

$$\hat{\boldsymbol{g}}_i = \frac{J_{i+} - J_{i-}}{2c_i} \begin{bmatrix} \frac{1}{\boldsymbol{\delta}_i[1]} \\ \vdots \\ \frac{1}{\boldsymbol{\delta}_i[p]} \end{bmatrix}, \tag{6.8}$$

where $\boldsymbol{\delta}_i\,[j]$ denotes the jth component of $\boldsymbol{\delta}_i$.

Consequently, the system parameters are updated according to the following formula:

$$\boldsymbol{\theta}_{i+1} = \boldsymbol{\theta}_i - a_i \hat{\boldsymbol{g}}_i \tag{6.9}$$

where a_i is a positive learning gain.

The convergence of parameters to the global optimal is subject to satisfactions of several assumptions on the considered system and the configurations of algorithmic parameters [67]. The important conditions required on a_i and c_i are as follows:

1. $a_i > 0$, $a_i \to 0$ as $i \to 0$, and $\sum_{i=0}^{\infty} a_i = \infty$

2. $c_i > 0$, $c_i \to 0$ as $i \to 0$, and $\sum_{i=0}^{\infty} (\frac{a_i}{c_i})^2 < \infty$

In this chapter, a_i and c_i are set as:

$$a_i = \frac{a_0}{(i + A + 1)^\alpha} \tag{6.10}$$

$$c_i = \frac{c_0}{(i + A)^\gamma}, \tag{6.11}$$

where A, a_0, a_0, α and γ are constant parameters.

Note that, in real implementations, the estimated system gradient $\hat{\boldsymbol{g}}_i$ is contaminated by system noises and disturbances in the freeway system. Even though, the *SPSA* based parameter learning algorithm is able to direct the updating of parameters towards directions with reduced cost function. The randomized perturbation vector also introduces randomness into the estimated gradient, and such randomness is beneficiary for

Tab. 6.3: Parameters of the *SPSA* based parameter learning algorithm.

α	γ	a_0	A
0.602	0.201	0.15	1

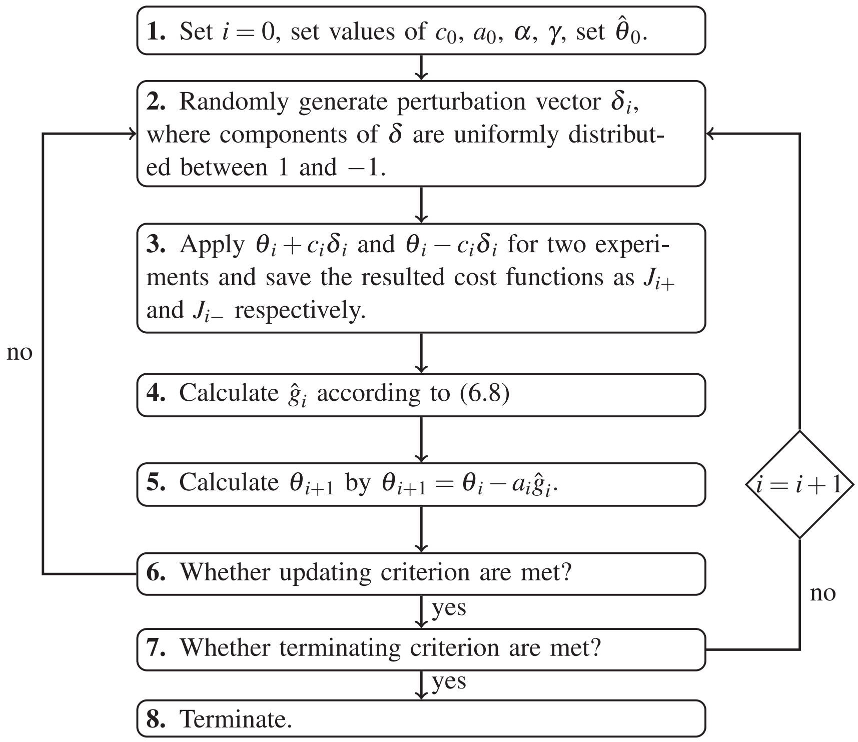


Fig. 6.3: The flow chart of the *SPSA* based parameter learning algorithm.

the parameter updating to escape from local minimum solutions. The parameters in the *SPSA* based parameter learning algorithm are summarized in Tab. 6.3.

Note also that parameters of the *FLC* based coordinative decision making algorithm are kept unchanged once the experiment starts, this way the appropriateness of these parameters can be evaluated throughout the whole period of freeway operation. The parameters are updated at the end of each iteration, e.g. when cost functions associated with $\boldsymbol{\theta}_{i+}$ and $\boldsymbol{\theta}_{i-}$ are obtained, and communication between the control center and the local controllers is needed only when the overall cost function is to be calculated and the parameter updating signals are transmitted. These data transmission tasks can be carried out when the ramp metering system stops working, for instance, they can be done during midnight times, when traffic load is extremely light and no ramp metering is needed. This arrangement of data transmission and parameter updating tasks keeps the normal freeway operation uninterrupted.

6.4 Numerical Example

6.4.1 Simulation Setup

To validate the proposed cooperative distributed ramp metering approach, a freeway network shown in Fig. 6.4 is considered. A benchmark freeway network consisted of 10 mainstream sections, 2 on-ramp links, and 1 off-ramp link is considered. The layout of the freeway model considered is provided in Fig. 6.4. All mainstream sections have 3 lanes and all on-ramp and off-ramp links have a single lane. The two on-ramp links are connected with section 4 and 8 at the beginning location, the off-ramp link is connected with section 5 at the ending position.

METANET model is used to simulate the freeway system, and the model parameters are listed in Tab. 6.4. The traffic demand profiles are given in Fig. 6.5. A total time of 3 hours is considered. A traffic volume at 5000 veh/hour is considered during the peak traffic hours on the freeway mainstream, which drops to 1500 veh/hour at a later time. The traffic demands at the two on-ramp links and the off-ramp link also consider peak hour traffic. Random noise with amplitude 10% of the above demand is imposed in the simulations.

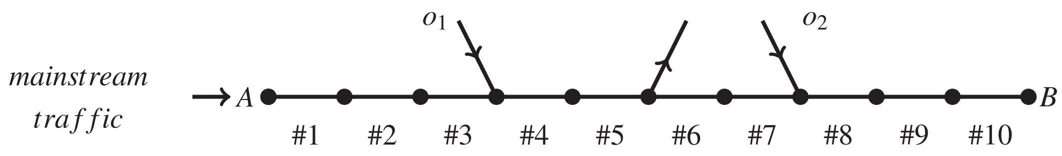


Fig. 6.4: Layout of the benchmark freeway network model.

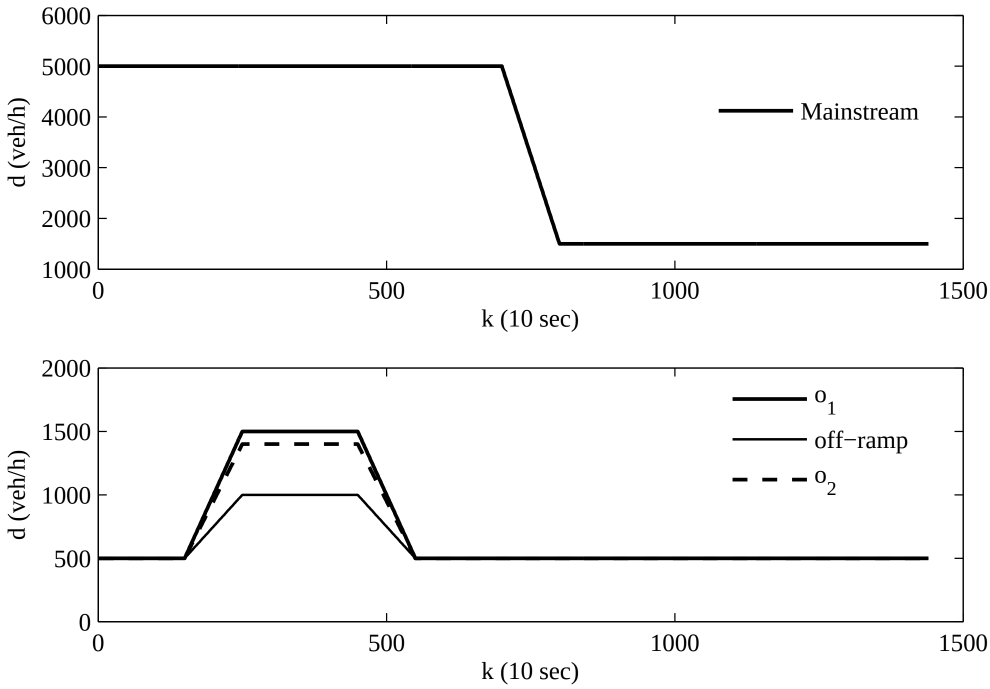


Fig. 6.5: Traffic demand.

Tab. 6.4: METANET model parameters.

v_f $km/hour$	ρ_c $veh/lane/km$	ρ_{max} $veh/lane/km$	a	μ $km^2/hour$
110	33.5	180	1.636	60
ϕ $veh/lane/km$	β $km/hour$	P	T $second$	L km
40	10	60	10	0.5

The following three scenarios are investigated in the simulation studies:

No control Case No ramp metering is applied at the on-ramp links.

ALINEA case *ALINEA* based ramp metering strategy is used for local freeway ramp metering at both on-ramp links, where the critical mainstream density, ρ_c, is used as the reference mainstream density.

LCRM case The *FLC* based local coordinative ramp metering strategy is used to determine the desired mainstream densities at each on-ramp link, and the *ALINEA* based algorithm is used to track these desired mainstream densities locally at the corresponding on-ramp links.

6.4.2 Results and Discussions

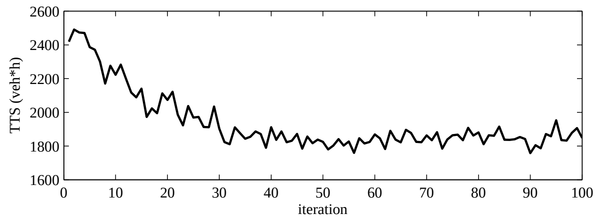


Fig. 6.6: Evolution of TTS.

The evolution of TTS values in 100 iterations are shown in Fig. 6.6. As shown, the value of TTS in the first iteration is around 2450 $veh \cdot h$, which is also the TTS associated with *ALINEA* based strategy. TTS is reduced to around 1800 $veh \cdot h$ after 100 iterations. Note that after about 50 iteration, the good TTS value has been achieved.

Based on these results, the following summaries can be made on the above results:

- Although the evolution of TTS is fluctuated due to the freeway system noise, significantly improved efficiency is obtained by the propose parameter tuning algorithm in terms of reduced TTS. This show the great potential of the proposed method for networked freeway ramp metering problem.

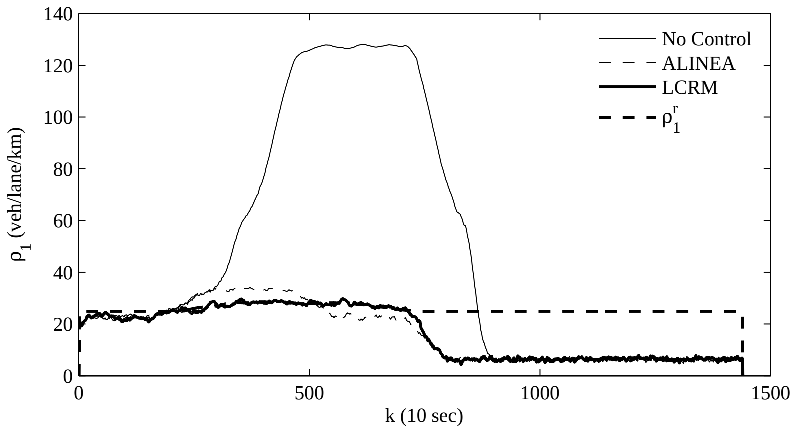
- Reduction of TTS by the *SPSA* based parameter learning scheme is fast, i.e. the minimum is achieved after only 50 iterations. This demonstrates the efficiency of the parameter learning algorithm.

The average TTS obtained from 30 independent experimental trials are 3205.8 ($veh \cdot h$), 2428.4 ($veh \cdot h$), 1859.7 ($veh \cdot h$) for the no control case, $ALINEA$ based ramp metering case and $LCRM$ based control case respectively. By the proposed algorithm, the TTS is reduced by 42% compared with that of no control case, and by 23.4% compared with that of $ALINEA$ case. It is clear that significantly improved efficiency of the ramp metering system has been achieved by the proposed method.

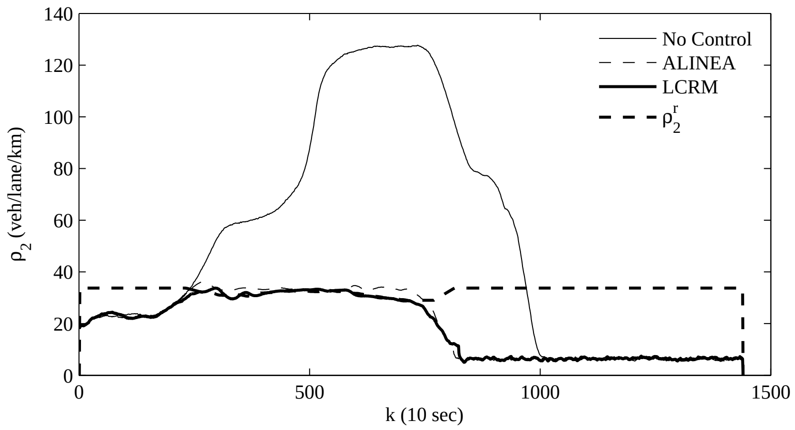
The profiles of mainstream densities of section 4 and 8 are shown in Fig. 6.7. The profiles of on-ramp queue volumes are shown in Fig. 6.8. Based on these results, the following findings are summarized:

- Although $ALINEA$ based strategy effectively prevents traffic congestions on the freeway mainstream, high on-ramp queue volumes are created. This is unfair to vehicles on the on-ramp link, because they have to spent more time waiting on the on-ramp link.

- The on-ramp queue volume at on-ramp 1 is effectively reduced by the $LCRM$ s-trategy. During the congestion period, the mainstream density around on-ramp link 1 is set lower than the critical density when mainstream density approaches the critical density and vehicles begin to queue up around on-ramp link 2. This is obviously an inefficient strategy with a local ramp metering perspective, because queue is created at on-ramp 1 when queuing vehicles could have been released into the mainstream to achieve higher traffic flow rate on the mainstream. However, this strategy reserves more capacity on the freeway mainstream link so that more vehicles from on-ramp link 2 can be merged, which will not only prevent the occur-



(a) Density profile at section 4.



(b) Density profile at section 8.

Fig. 6.7: Mainstream density profiles. *No Control*: Without control, severe congestion occurs on the freeway mainstream. Mainstream density at section 4 rises to over 120 veh/lane/km during the time from $k = 450$ to $k = 750$. At section 8, mainstream traffic is also congested with densities over 120 veh/lane/km during the time from $k = 500$ to $k = 750$. *ALINEA*: Mainstream congestion is not incurred and the mainstream densities at section 4 and 8 closely track the critical density value, except that mainstream density at section 4 drops below the critical density at $k = 500$. *LCRM*: Mainstream density at section 4 is kept around a value which is lower than the critical density throughout the whole congestion period. The mainstream density at section 8 is closely tracks the critical density during the time from $k = 250$ to $k = 600$. After $k = 600$, density in section 8 slowly decreases.

rence of traffic congestion, but also reduce the on-ramp queue volume at on-ramp link 2.

- The local controllers work as *ALINEA* based local ramp metering controllers except that the reference mainstream densities are coordinately determined with mild requirement on communication among local controllers. The significantly improved system efficiency at the system level demonstrates that limited local coordination strategy is quite effective for networked freeway ramp metering systems.

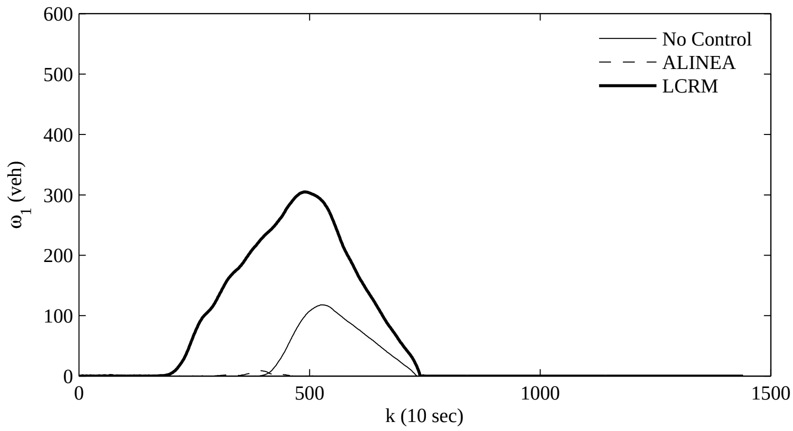
- Using the *LCRM* strategy, on-ramp queue volumes at the two on-ramp links are limited within a moderate level, i.e. below 300 vehicles, which makes the ramp metering system fairer to vehicles from the on-ramps compared with that of *ALINEA* case. Particularly, queue volume at on-ramp link 2 are significantly reduced during the congested period, resulting in shorter waiting time spent by vehicles there.

- The queue volumes at the two on-ramp links are comparable in terms of their amplitudes and durations. This indicates that the resulted ramp metering strategy is quite fair to vehicles from both on-ramp links. The *ALINEA* based strategy is unable to achieve such an equity among vehicles from different on-ramps, i.e. high queue volume is created at on-ramp 2, while only a minor queue volume is created at on-ramp 1.

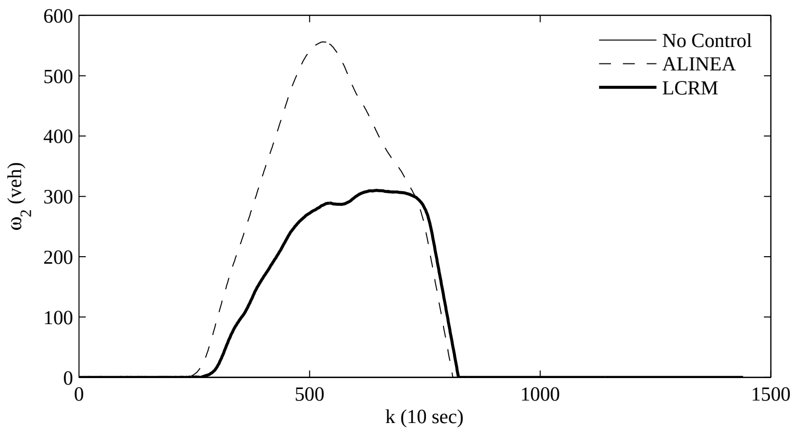
6.5 Further Discussions on Equity Issues

6.5.1 Case Studies

In the above case studies, $\omega_{max} = 250$ vehicles is used for both on-ramp links in all cases, which means that the two on-ramp links are treated as equally important.



(a) On-ramp queue volume at on-ramp link 1.



(b) On-ramp queue volume at on-ramp link 2.

Fig. 6.8: Profiles of on-ramp queue volumes. *No control*: Almost all vehicles from the on-ramp links are released into the freeway mainstream except that there is a small queue volume of about 120 vehicles at on-ramp link 1 around $k = 500$. *ALINEA*: There is a small queue at on-ramp link 1 around $k = 500$, but a large queue of about 550 vehicles is created at on-ramp link 2. *LCRM*: The a queue volume of about 300 vehicles is created at on-ramp link 1. The queue volume at on-ramp link 2 is significantly reduced with a maximum of about 300 vehicles. The queue at on-ramp link 1 is created at an earlier time than that at on-ramp link 2.

However, due to the variations in ramp storage capacities at different on-ramp links, different queue constraints might be needed in practice. To further investigate the influence of different settings of queue constraints on the performance of the proposed local coordinative ramp metering strategy, additional case studies are conducted.

Denote ω_{max}^1 and ω_{max}^2 as the queue constraints for on-ramp link 1 and 2 respectively. In the first set of cases, different values of equal constraints are used respectively. In the second set of cases, ω_{max}^1 is varied, while a number of ω_{max}^2 is applied. In the last set of cases, ω_{max}^1 is kept unchanged, while ω_{max}^2 is varied. A summary of the queue constraints values for each set of cases is shown in Tab. 6.5.

Tab. 6.5: Summary of queue constraints in additional case studies.

Set	Case	ω_{max}^1 (veh)	ω_{max}^2 (veh)	Set	Case	ω_{max}^1 (veh)	ω_{max}^2 (veh)	Set	Case	ω_{max}^1 (veh)	ω_{max}^2 (veh)
1	1	150	150	2	1	150	250	3	1	250	150
	2	200	200		2	200	250		2	250	200
	3	250	250		3	250	250		3	250	250
	4	300	300		4	300	250		4	250	300
	5	350	350		5	350	250		5	250	350

6.5.2 Results and Discussions

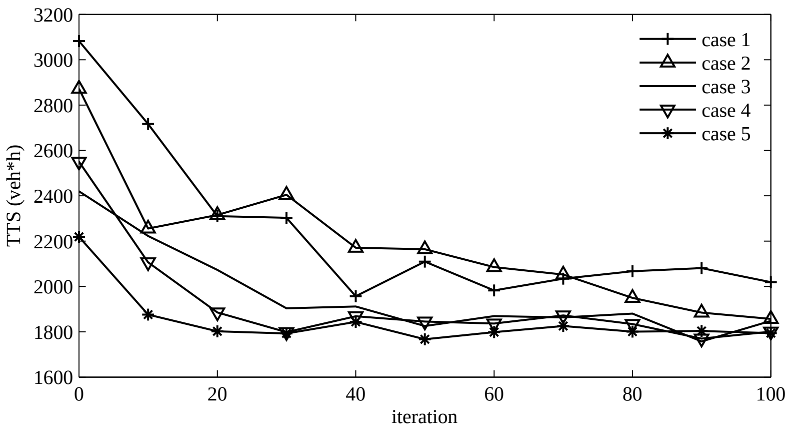


Fig. 6.9: Set 1: Evolution of TTS.

The evolution of TTS in case studies of set 1 are given in Fig. 6.9 and on-ramp queue volume profiles are shown in Fig. 6.10. The TTS values are reduced to the minimums

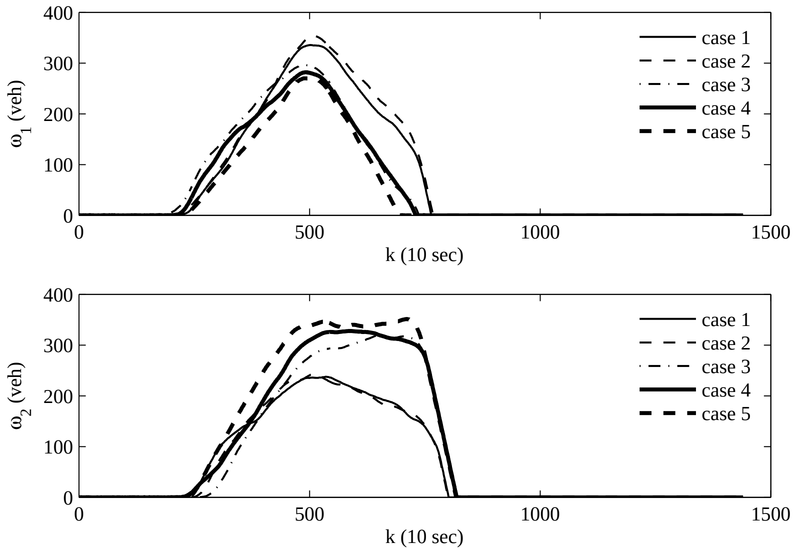


Fig. 6.10: Set 1: On-ramp queue volumes.

using the proposed strategy. This indicates that although different priorities are given to the two on-ramp links, the proposed method effectively finds the optimal balance between mainstream and on-ramp traffic to obtain the minimum system TTS.

Although the constraints on the on-ramp queue volumes are quite stringent in cases 1 and 2, i.e. lower maximum queue limit is used compared with that of other cases, the on-ramp queue volumes are not strictly kept below the maximum limits. Particularly, the queue volumes at on-ramp 1 reach the maximum of over 300 vehicles in both cases. The queue volumes at on-ramp 2 are lower than that at on-ramp 1, but maximum queue volumes of over 200 vehicles are created. This is probably because violations of the queue constraints will benefit the overall traffic system to avoid congestions on the mainstream. However, this doesn't mean that constraints on queue volumes should always be violated to gain such benefits. For instance, in case 5, the maximum queue limits are set as 350, which is never violated at both on-ramps.

It is worth mentioning that although the same queue constraints are applied at both on-ramps, the on-ramp traffic at on-ramp 1 has been sacrificed a bit to have higher queue volumes compared with that at on-ramp 2, when the constraint is stringent, i.e. ω_{max} is low.

Note that the minimum TTS value obtained in case 1 is higher than that obtained in cases 2 and 3. The lowest minimum TTS are obtained in cases 4 and 5. It is clear that as more stringent constraint on queue volumes leads to increased TTS. It is clear that when lower maximum queue limit is applied, more penalty is incurred due to the violation of queue constraints, although the proposed strategy has managed to find the optimal balances between the two on-ramps, and between on-ramp and mainstream traffic.

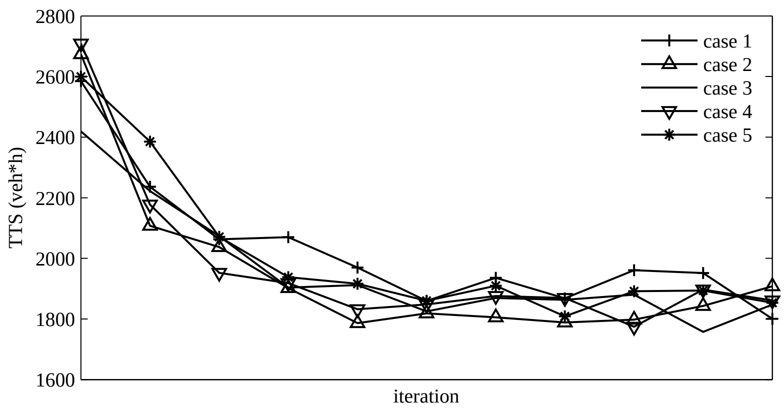


Fig. 6.11: Set 2: Evolution of TTS.

The evolution of TTS in case studies of set 2 are given in Fig. 6.11 and on-ramp queue volume profiles are shown in Fig. 6.12. Fig. 6.13 and Fig. 6.14 show the evolution of TTS in case studies of set 3 and the corresponding on-ramp queue volume profiles. TTS in both sets are reduced to the minimums, which are comparable in all cases. In set 3, when ω^1_{max} is fixed at 250 vehicles, as ω^2_{max} is increased, the queue volumes at on-ramp 1 is decreased while queue volumes at on-ramp 2 is increased correspondingly. This shows a strong correlation between the queue constraint at on-ramp 2 and the corresponding

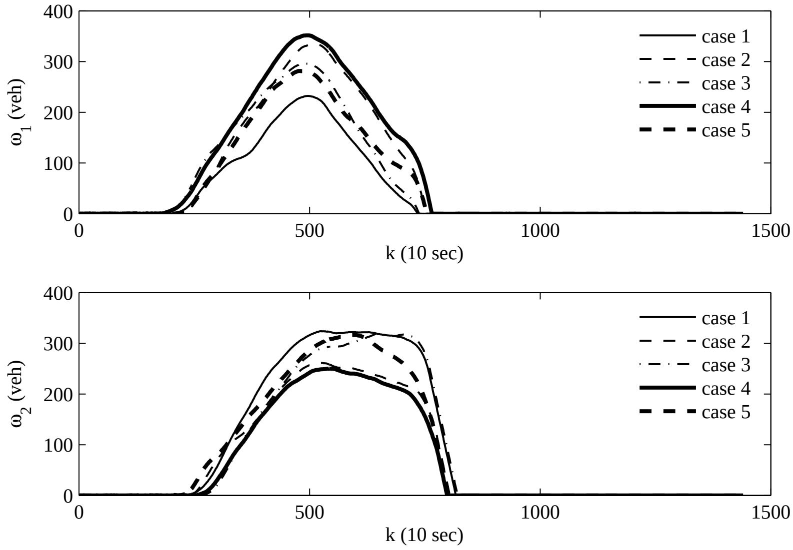


Fig. 6.12: Set 2: On-ramp queue volumes.

balance between the two on-ramp links. However, such a correlation is not identified in the results of case studies in set 2, where the on-ramp queue volumes at both on-ramps vary in an unclear manner.

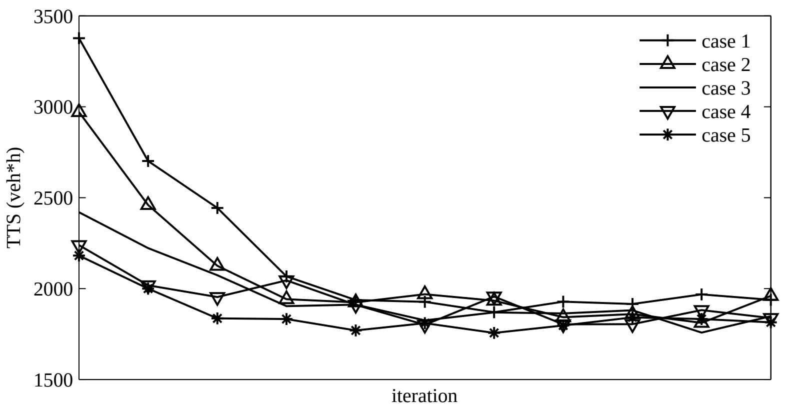


Fig. 6.13: Set 3: Evolution of TTS.

It is interesting to note that the profiles of total on-ramp queue volumes on both links are quite close in all cases, as shown in Fig. 6.15. This suggests that the total queue volumes on the on-ramp links and the total mainstream traffic volumes resulted

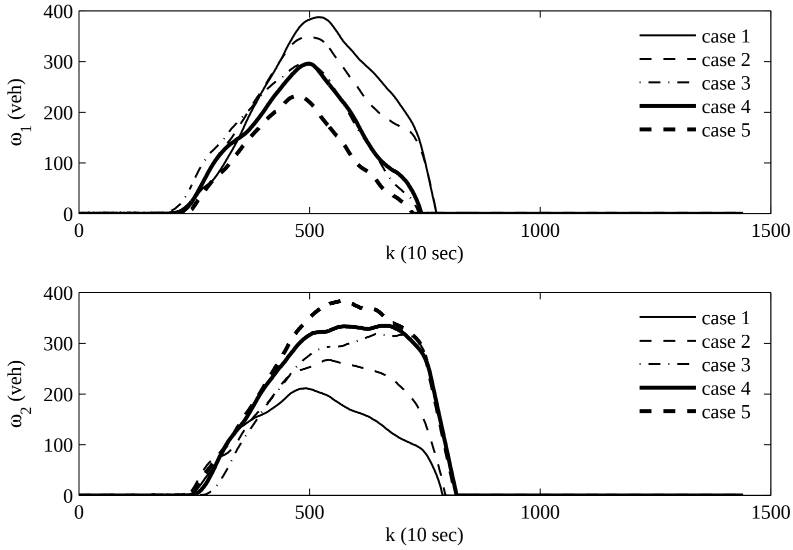


Fig. 6.14: Set 3: On-ramp queue volumes.

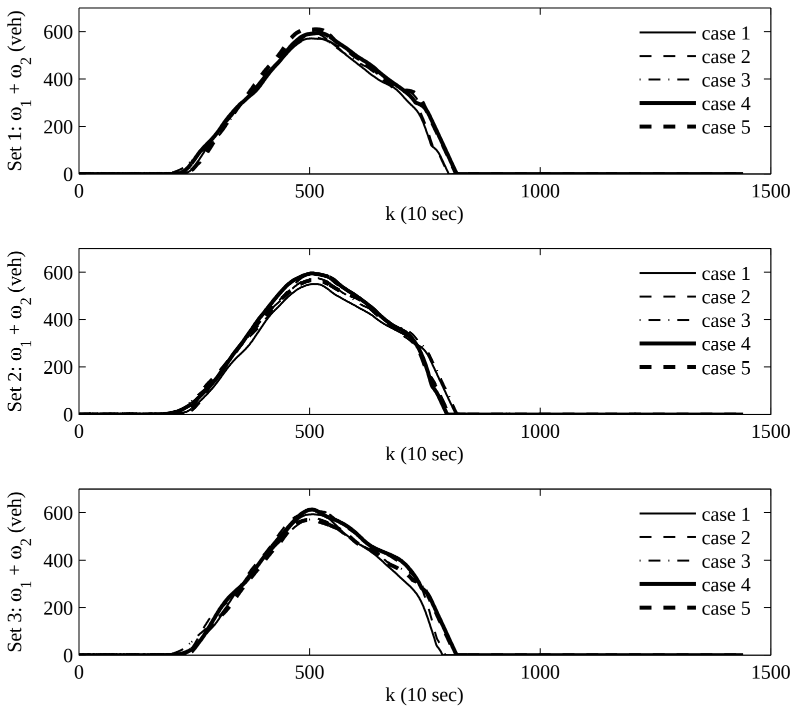


Fig. 6.15: Sum of on-ramp queue volumes.

from the proposed strategy are roughly unchanged, because of the repetitiveness of the total traffic volume. From a macroscopic perspective of view, this means that the balance between mainstream traffic and on-ramp traffic is also unchanged irrespective of the varied constraints on queue limits. It can be inferred from the above results that the overall performance of the proposed strategy is determined mainly by the balance between mainstream and on-ramp traffic. This is probably due to the severe consequence related with mainstream traffic congestions, e.g. sharply reduced traffic throughput on the mainstream, increased travel time and waiting time. Besides, the efficiency of coordinative ramp metering strategies would be when mainstream traffic is congested. For instance, when mainstream traffic congestion occurs around an on-ramp link, it will propagate towards the upstream direction on the freeway mainstream, which makes the neighboring mainstream areas congested also and the controller within the affected area won't be able to cooperate effective by ramp metering.

From the above results, the following main findings can be concluded:

1. The proposed strategy is able to find the optimal balance between traffic on the on-ramp links under varied settings of queue constraints, where the TTS is minimized.

2. Using the proposed strategy, variations in the settings of queue constraints can effectively adjust the queue volumes on the on-ramp links, which allows varied priorities among on-ramp links.

3. The optimal balances between mainstream and on-ramp traffic resulted from varied settings of queue constraints are similar at the macroscopic level.

6.6 Conclusions

In this chapter, a novel *FLC* based local coordinative ramp metering strategy is studied for networked freeway traffic control. Local traffic measurement information is exchanged among neighboring controllers through limited communication, based on which reference mainstream densities are coordinately determined by *FLC* based coordinative decision making algorithm. *ALINEA* based strategy is adopted by local controllers to track the reference mainstream densities. The parameters of the *FLC* algorithm are tuned by a simple *SPSA* based parameter learning algorithm, which effectively finds the optimal coordinative decision making policies without interruption to normal freeway operations. Using the proposed strategy, limited communication among neighboring controllers is required rather than continuous communication between the control center and all local controllers. This reduces the communication cost of existing centralized control based strategies. Furthermore, the structure of the proposed strategy is quite simple and no complex model based computation is involved. The efficiency of coordinated freeway ramp metering system is significantly improved in case studies. In particular, using the proposed local coordinative ramp metering strategy, the *TTS* is reduced by over 48% compared with no control case, and by over 18% compared with *ALINEA* based ramp metering case. This study shows the great potential of the proposed strategy for coordinated freeway ramp metering problems.

The study presented in Chapter 6 extends the FLC based ramp metering strategies by applying it for coordination among multiple controllers within a freeway network. The combination of FLC and SPSA based parameter learning is further demonstrated to be effective for solving optimal control problems. It is worth pointing out that the proposed approach falls into the framework of decentralized and cooperative control, because there is no centralized decision making units in the control system, which complements existing studies on networked freeway ramp metering systems.

In the next chapter, the networked freeway ramp metering problem is addressed by another novel and efficient strategy, which considers the networked freeway ramp metering problem as a macroscopic traffic scheduling problem. A macroscopic traffic scheduling (MTS) strategy is proposed which utilizes the strengths of fixed-time traffic scheduling strategies and the feedback based ramp metering. The considered time is divided into macroscopic time periods, for which reference mainstream density signals are scheduled at each on-ramp controller. The feedback based reference tracking algorithm is used by local controllers for drive the mainstream densities to track these scheduled reference signals. To obtain the optimal system performance, an SPSA based parameter learning algorithm is used to find the optimal scheduling plan of the reference mainstream density signals.

Different from the LCRM strategy proposed in last chapter, the MTS strategy solves the networked freeway ramp metering problem as an off-line optimization problem with consideration to system randomness and disturbances. (It is also suitable for implementation requiring realtime parameter tuning due to the effectiveness of SPSA in dealing with randomness and disturbances.) Therefore, the reference signals are fixed before each operation trial, not like that of LCRM case where reference signals are varied according to realtime traffic conditions and the coordination policies. Additionally, communication is required neither among individual controllers nor between the controllers and a control center during the operation time. These unique features of the MTS strategy reduces the system complexity and implementation cost.

However, MTS and LCRM shares some common feature, e.g. they both utilize the repetitiveness of freeway traffic and aim at optimization of the network wide freeway traffic flow to obtain minimum TTS. Furthermore, decision variables are all tuned at the macroscopic level by minimizing the system cost function.

Chapter 7

Networked Freeway Ramp Metering Using Macroscopic Traffic Scheduling and SPSA based Parameter Learning

7.1 Introduction

Freeway traffic control is an active research area in modern intelligent transportation systems due to the emerging environmental and societal issues resulted from traffic congestions. Previous works on freeway traffic control mainly focused on ramp metering, which was reported to be effective in reducing freeway congestions and improving freeway traffic conditions [26].

Freeway ramp metering is realized by implementing a traffic light at the freeway on-ramp entries to regulate the traffic flow merging into freeway mainstream. Mainstream freeway traffic condition is closely related with the merging traffic flow from on-ramp links, therefore, mainstream traffic conditions can be regulated by regulating the merging behaviors of on-ramp traffic. According to the fundamental diagram, as shown in Fig. 1.4, which shows the empirical relationship between average mainstream traffic flow and density under homogeneous traffic conditions. The maximum mainstream traffic flow is obtained when mainstream density is at the critical density.

Existing ramp metering strategies generally fall into two categories: fixed time s-trategies and traffic responsive strategies. Fixed time ramp metering strategies adopt fixed ramp metering signals at specific times, and these signals are derived based on historical data rather than realtime traffic situations [79, 80]. The fixed time ramp metering strategies are inefficient and sometimes counterproductive [27]. The basis for fixed time ramp metering strategy is that daily freeway traffic is generally repeated, therefore, historical freeway data can be used for proper scheduling the ramp metering signals to improve the efficiency of freeway systems, e.g. mitigate or prevent freeway congestion, reduce the travel times. This strategy may incur problems due to the uncertainties in freeway traffic systems. For instance, we can consider the situation that the historical traffic volume entering the freeway mainstream from an on-ramp link between 7AM and 7:10AM is 300 vehicles. However, due to system randomness, traffic volume entering the freeway within the first and second 5 minutes can be (a): 50 and 250 vehicles, or (b): 150 and 150 vehicles. Apparently, these are two different traffic conditions, i.e. the mainstream traffic will be more violently impacted by the sharply increased merging flow in case (a) that by the smooth merging flow in case (b), although the average traffic flow rates within the 10 minutes time interval are the same in both cases. In face of such randomness in freeway traffic, a fixed time ramp metering strategy will not be able to guarantee a consistent performance. This is because an important feature of the freeway traffic repetitiveness is that it is a macroscopic level behavior rather than a microscopic one. Hence, to utilize the repetitiveness in freeway traffic, traffic scheduling should be conducted at the macroscopic level correspondingly. It is worth pointing out that although fixed time ramp metering strategies are limited in their efficiency, they possess important features which are favorable in real implementations. For example, fixed time ramp metering strategies have simple controller structure and require no realtime traffic measurement and online computation.

Traffic responsive ramp metering strategies determine the ramp metering signals from realtime traffic conditions to cope with varied traffic conditions. Among various traffic responsive ramp metering algorithms, the *ALINEA* algorithm and its variants are reported to be effective in improving freeway mainstream traffic flow in filed implementations [33]. The key idea of *ALINEA* based ramp metering is that maximum mainstream traffic flow is obtained by maintaining the mainstream density at the critical density, as suggested by the fundamental diagram. A feedback control based algorithm is adopted by *ALINEA* for maintaining mainstream traffic density at the critical density. *ALINEA* can either be used as a local ramp metering algorithm to maximize local mainstream traffic flow, or as a local reference mainstream density tracking algorithm, where the reference signals are determined by system level coordinated ramp metering algorithms.

Recently, networked freeway ramp metering problems have aroused huge research interests among researchers. The networked freeway ramp metering is a challenging problem due to the networked nature of the freeway systems, the complex interactions among subsystems, and the uncertainties in freeway systems. Model predictive control (*MPC*) based approaches were studied for ramp metering of networked freeway systems [28, 37]. The optimal freeway states in the whole freeway network, i.e. mainstream densities around the on-ramp entries and the speed limit signals, are calculated with respect to a period of time into the future (denoted as t_1). The calculated freeway states are subsequently used as reference signals to tracked by local ramp metering controllers. The optimal state variables are recalculated after another period of time (denoted as t_2, and $t_1 >> t_2$). Another MPC based method was used for ramp metering of networked freeway systems, where a genetic fuzzy logic control approach was proposed [49]. It should be noted that MPC based methods require continuous computational power for calculating the optimal traffic states. When the size of the freeway network increases, there are a large number of system states to be optimally specified, which is quite a challenging task so far.

Although randomness and uncertainties exist in freeway traffic, strong repetitiveness exists in the freeway traffic system on the macroscopic level, i.e. there are daily morning peak hours from 6 AM to 9 AM and evening peak hours from 5 PM to 8 PM. Several researches were conducted to make use of the repetitiveness of freeway traffic for ramp metering purposes. An iterative learning control (ILC) based ramp metering method was studied for driving the mainstream traffic density to track the critical density [62]. Traffic at off-ramp links are considered as unknown but repeated disturbance, and accurate tracking is achieved by iteratively learning from the result of previous control trial.

In real implementation of freeway ramp metering systems, it is desirable that efficiencies of the simple ramp metering algorithms can be improved while retaining their strengths. Driven by this thinking, a novel hybrid method combining the fixed time strategy based traffic scheduling with $ALINEA$ based traffic responsive ramp metering is proposed for networked freeway ramp metering. By the proposed method, freeway traffic are macroscopically scheduled in the time domain. This scheduling approach makes use of the macroscopic repetitiveness in freeway traffic. Different from existing fixed time ramp metering strategies, the reference mainstream density signals are scheduled instead of fixed time ramp metering signals, and traffic scheduling is conducted at the macroscopic level, i.e. the reference signals are defined for time periods comprised of multiple time intervals. The *ALINEA* based local ramp metering algorithm is adopted to track the reference signals. Since the performance of the proposed method depends on the scheduled reference signals, these reference signals are regarded as decision variables, which are tuned by an *SPSA* based parameter learning algorithm to achieve the optimal system performance. The *SPSA* based parameter learning algorithm makes observations on the performance of historical operation trials and learns from the system gradient to effectively direct the updating of parameters. Compared with networked ramp metering methods requiring continuous computational power, e.g. MPC based methods, the implementation cost of the proposed method is comparable with that of *ALINEA* based local ramp metering systems. Although communication between local controllers and a control center is needed due to its centralized control nature, yet data transmission is carried out only after each trial of freeway operation for updating of cost functions and reference signals. Regular communication between local controllers and the control center is unnecessary, therefore, the communication cost is greatly reduced. Most importantly, the parameter learning task can be performed without disturbing the normal freeway operations, and is suitable for realtime implementations.

The chapter is organized as follows. Background knowledge and formulation of the optimal networked freeway ramp metering problem are given in Section 7.2. The proposed macroscopic traffic scheduling based ramp metering method and *SPSA* based parameter learning algorithm are described in Section 7.3. Case studies are conducted in Section 7.4. Section 7.5 concludes the chapter.

7.2 Problem Formulation

7.2.1 METANET Model Revisit

The freeway traffic flow process is highly complex, and can be described by macroscopic models comprised of nonlinear equations [1, 2, 5, 23]. Among these models, the *METANET* model is most widely used [5]. In *METANET* model, the freeway mainstream link is divided into small sections, where each section can be connected with an on-ramp and/or off-ramp link. An example of the mainstream section model is given in Fig. 7.1. The complete model describes the spatial and temporal relationships between the main state variables, e.g. average mainstream traffic density and flow, mean traffic speed. The main mathematic equations involved are as follows:

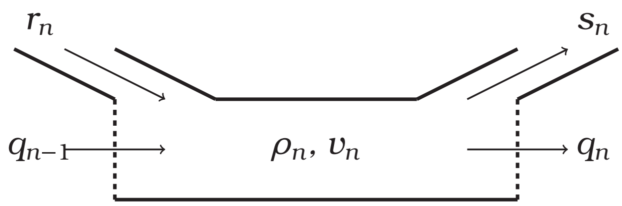


Fig. 7.1: Freeway mainstream section model.

$$\rho_n(k+1) = \rho_n(k) + \frac{T}{L_n}[q_{n-1}(k) - q_n(k) + r_n(k) - s_n(k)] \tag{7.1}$$

$$q_n(k) = \rho_n(k) v_n(k) \tag{7.2}$$

$$\begin{aligned} v_n(k+1) = v_n(k) &+ \underbrace{\frac{T}{\tau}\left[V\left(\rho_n(k)\right) - v_n(k)\right]}_{\text{relaxation term}} \\ &+ \underbrace{L_n v_n(k)\left[v_{n-1}(k) - v_n(k)\right]}_{\text{convection term}} \\ &- \underbrace{\frac{T\mu}{L_n\tau}\frac{[\rho_{n+1}(k) - \rho_n(k)]}{[\rho_n(k) + \psi]}}_{\text{anticipation term}} \end{aligned} \tag{7.3}$$

$$V\left(\rho_n(k)\right) = v_f\,\boldsymbol{exp}\left(-\frac{1}{a}\left(\frac{\rho_n(k)}{\rho_c}\right)^a\right), \tag{7.4}$$

where the variables are defined as:

n index of mainstream sections, $n \in [1, N]$ and N is the total number of mainstream sections;

k index of discrete time step, $k \in [0, K]$ and K is the total number of time steps;

T period of sampling ($hour$);

ρ_n average density within section n, (veh/km);

v_n mean speed of vehicles within section n, ($km/hour$);

q_n volume of vehicles from section n to $n+1$, ($veh/hour$);

r_n inflow volume of vehicles at on-ramp of section n, ($veh/hour$);

s_n outflow volume of vehicles at off-ramp of section n, ($veh/hour$);

v_f free flow speed of vehicles, the speed of vehicles under zero mainstream density, ($km/hour$);

ρ_c the critical mainstream density, (veh/km);

L_n length of section n, (km);

τ a time constant, reflecting the reaction speed of drivers, ($hour$);

μ, ψ, and a are all constant parameters, reflecting the characteristics of geometry of freeway roads, vehicle types and driver behaviors. (7.1) is the density equation which shows the conservation law of vehicles. (7.2) expresses the relationship between average traffic flow, density and space mean speed. (7.3) is the equation that determines the speed variation from k to k+1. The speed variation is determined by three terms: the relaxation term showing that mainstream traffic speed intends to follow a target value determined by the fundamental relationship between density and speed under homogeneous traffic conditions, the convection term showing contribution of upstream section traffic to the speed dynamics, and the anticipation term reflecting influence of downstream traffic to speed dynamics of the current section. Note that exponential nonlinearity exists in (7.4), the last three terms and (7.2) are all nonlinear, making the complete model complexly parameterized by the following model parameters

$$\boldsymbol{\phi} = [v_f \ \rho_c \ a \ \mu \ \psi \ \tau]^T .$$

The evolution of queue volume on the on-ramp links is described by:

$$\omega(k+1) = \omega(k) + T(d(k) - r(k)), \tag{7.5}$$

where $d(k)$ denotes the flow rate of traffic demand at the on-ramp link.

Additional terms can be added to (7.3) to capture the impact of merging flow and lane drop to mean traffic speed on the mainstream link [71].

7.2.2 ALINEA based Ramp Metering

ALINEA is the most well-known ramp metering algorithm which was proposed by Markos Papageorgiou in the 1990s. The *ALINEA* control law is expressed as:

$$r(k+1) = r(k) + \beta(o^* - o(k)). \tag{7.6}$$

The flow rate of merging traffic should not exceed the maximum traffic flow available at the on-ramp link, where the maximum flow rate is calculated as:

$$r^{\omega}_{max}(k+1) = d(k) + \frac{\omega(k)}{T}. \tag{7.7}$$

An additional constraint is imposed on the maximum allowable flow rate from the on-ramp link due to considerations of traffic condition in the mainstream. This constraint is calculated as:

$$r^{o}_{max} = Q_o \frac{\rho_{max} - \rho(k)}{\rho_{max} - \rho_c}, \tag{7.8}$$

where Q_o is the maximum flow rate achievable on the on-ramp link under free-flow conditions, and ρ_{max} is the maximum density on the mainstream. To prevent the ramp metering signal from exceeding these physical limit of ramp flow rate, a modified ALINEA algorithm with constraint on the overall ramp metering signal is expressed as:

$$r^l(k+1) = \max\{\min[r(k) + \beta(o^* - o(k)),\ r_{\max}(k+1)],\ r_{\min}\}, \tag{7.9}$$

where $r_{\min}$ is set to be a nonzero value to prevent total close-up of the on-ramp entry, and $r_{\max}(k+1) = \min\{r^{\omega}_{max}(k+1), r^{o}_{max}(k+1)\}$ is the maximum allowable flow rate. More detailed settings on constraints of ramp metering signal were discussed [28].

To prevent the formation of high queue volume on the freeway on-ramp link and improve the equity of freeway ramp metering, constraints can be enforced to prevent the queue volume from exceeding predefined limits. Denote ω_{max} as the limit on queue volume, *ALINEA* ramp metering with queue constraints can be expressed as:

$$\begin{aligned} r(k+1) &= max\{r^l(k+1),\ r^{\omega}(k+1)\} \\ r^{\omega}(k+1) &= d(k) - \frac{\omega_{max} - \omega(k)}{T}. \end{aligned} \tag{7.10}$$

Detailed explanation on ramp metering and queue constraints strategies are discussed in [35]

7.3 Optimal Macroscopic Freeway Traffic Scheduling with Parameter Learning

7.3.1 Networked Freeway Ramp Metering Problem

Let the considered freeway mainstream link be comprised of N sections indexed by n, and denote λ as the index of on-ramp link, $\lambda \in [1,\ \lambda_m]$, where λ_m is the total number of on-ramp links. Denote the on-ramp merging flow rate at on-ramp link λ at time step k as $r_\lambda(k)$. The optimal networked freeway ramp metering task is to seek a set of control profile:

$$\Big\{r_\lambda(k):\ k \in [1,\ K],\ \lambda \in [1,\ \lambda_m]\Big\}, \tag{7.11}$$

such that the optimal ramp metering performance is obtained.

7.3.2 The Macroscopic Traffic Scheduling Strategy

Let the considered K time intervals be equally divided into n_p periods and denote p as the index of the time periods. By the macroscopic traffic scheduling strategy, reference mainstream densities are specified for each time period at each on-ramp link. These reference signals are the desired mainstream density to be maintained accordingly by local ramp metering controllers.

Denote $\rho^r_\lambda(p)$ as the scheduled reference mainstream density at on-ramp link λ in the pth period. Denote $\rho_\lambda(k)$ and $r_\lambda(k)$ as the mainstream density and on-ramp merging flow rate at on-ramp link λ during time interval k. The on-ramp merging flow rate at at on-ramp link λ is then determined as:

$$r_\lambda(k+1) = r_\lambda(k) + \beta\left(\rho^r_\lambda(k) - \rho_\lambda(k)\right) \tag{7.12}$$

$$\rho^r_\lambda(k) = \rho^r_\lambda(p),\ if\ \frac{(p-1)K}{n_p} + 1 \leq k < \frac{pK}{n_p}. \tag{7.13}$$

It is clear that the performance of the ramp metering system using the macroscopic traffic scheduling strategy depends on the vector of decision variables:

$$\boldsymbol{\theta} = [\rho^r_1(1)\ \cdots\ \rho^r_1(n_p)\ \cdots\ \rho^r_{\lambda_m}(1)\ \cdots\ \rho^r_{\lambda_m}(n_p)]^T. \tag{7.14}$$

7.3.3 Cost function

The total time spent (TTS) by all vehicles within the whole network, is commonly used to evaluate the efficiency of the ramp metering system. TTS based cost function is expressed as:

$$J = T \sum_{k=1}^{K} \left\{ \sum_{n=1}^{N} \rho_n(k) \delta_n L_n + \sum_{\lambda=1}^{\lambda_m} \omega_\lambda(k) \right\}, \tag{7.15}$$

where T is the length of time interval, δ_n is the number of lanes in section n, and L_n is the length of the nth section.

An additional term is usually included in the performance index to apply penalty on overlong queues at on-ramps. This term reflects equity considerations to prevent long queues at on-ramp links, which also prevents severe intervention to urban surface street traffic. The *TTS* based cost function with penalty terms is expressed as:

$$J = T \sum_{k=1}^{K} \left\{ \sum_{n=1}^{N} \rho_n(k) \delta_n L_n + \sum_{\lambda=1}^{\lambda_m} \omega_\lambda(k) + \alpha_\omega \sum_{\lambda=1}^{\lambda_m} \Big(\max\big(0, (\omega_\lambda(k) - \omega_{\lambda,max})\big) \Big)^2 \right\}, \tag{7.16}$$

where α_ω is the weight for the penalty term on on-ramp queue volume, $\omega_{\lambda,max}$ is a threshold queue volume and any queue volume higher than this value would be penalized.

It is important to note that smooth reference mainstream density signals are desirable in the macroscopic traffic scheduling problem. This is because abrupt changes in the scheduled reference density signals will cause violent fluctuations in the traffic flow both on the mainstream and on-ramp links during the transitional time between consecutive periods. For this reason, another term is included in the *TTS* based cost function in (7.16) to penalize variations in the scheduled reference signals.

In this paper, a revised cost function including penalty terms on on-ramp queue volumes and variations of reference signals is used, which is expressed as:

$$\begin{aligned} J = T \sum_{k=1}^{K} &\left\{ \sum_{n=1}^{N} \rho_n(k) \delta_n L_n + \sum_{\lambda=1}^{\lambda_m} \omega_\lambda(k) + \alpha_\omega \sum_{\lambda=1}^{\lambda_m} \Big(\max\big(0, (\omega_\lambda(k) - \omega_{\lambda,max})\big) \Big)^2 \right\} \\ &+ T \sum_{p=2}^{n_p} \sum_{\lambda=1}^{\lambda_m} \alpha_r \big(\rho_\lambda^r(p) - \rho_\lambda^r(p-1)\big)^2, \end{aligned} \tag{7.17}$$

where α_r is a constant weight. Note that $\rho^r_\lambda(p) - \rho^r_\lambda(p-1)$ is the change in reference density signal at on-ramp link λ from period $p-1$ to period p.

7.3.4 Objective

Based on the above formulation, performance of the macroscopic traffic scheduling strategy depends on the scheduled reference mainstream density profile $\boldsymbol{\theta}$. $\boldsymbol{\theta}$ directly influences the mainstream density profiles and on-ramp volume profiles, i.e. $\rho_n(k)$ and $\omega_\lambda(k)$ in (7.17). Hence the system performance (in terms of TTS), can be adjusted by tuning $\boldsymbol{\theta}$.

The objective of macroscopic freeway traffic scheduling is to seek the optimal $\boldsymbol{\theta}$ such that the cost function, i.e. J in (7.17), is minimized.

7.3.5 SPSA Based Parameter Learning

Due to the efficiency of the *SPSA* algorithm for parameter tuning and optimization tasks, it has been widely used in various fields. In this chapter, we adopt the simultaneous perturbation stochastic approximation method to solve the macroscopic traffic scheduling problem.

Denote i as the index of iterations, $\boldsymbol{\theta}_i$ as the parameter vector in the ith iteration. At each iteration, i.e. i, the following procedures are followed by the *SPSA* based parameter learning algorithm:

1. A perturbation vector is generated as $\boldsymbol{\Delta}_i = c_i \boldsymbol{\delta}_i$, where c_i is a positive constant and $\boldsymbol{\delta}_i$ is of the same dimension as $\boldsymbol{\theta}$ with its components randomly chosen from 1 and -1.

2. Two experimental operation trials are conducted using parameter vectors $\boldsymbol{\theta}_i^+ = \boldsymbol{\theta}_i + \boldsymbol{\Delta}_i$ and $\boldsymbol{\theta}_i^- = \boldsymbol{\theta}_i - \boldsymbol{\Delta}_i$ respectively.

3. Denote the corresponding cost functions resulted from these two experimental trials as J_i^+ and J_i^-. An estimated gradient is calculated by:

$$\hat{\boldsymbol{g}}_i = \frac{J_i^+ - J_i^-}{2c_i} \begin{bmatrix} \frac{1}{\boldsymbol{\delta}_i[1]} \\ \vdots \\ \frac{1}{\boldsymbol{\delta}_i[j]} \\ \vdots \\ \frac{1}{\boldsymbol{\delta}_i[Mp_{max}]} \end{bmatrix}, \tag{7.18}$$

where $\boldsymbol{\delta}_i[j]$ denotes the jth component of $\boldsymbol{\delta}_i$.

4. Set $\boldsymbol{\theta}_{i+1} = \boldsymbol{\theta}_i - a_i\hat{\boldsymbol{g}}_i$, where a_i is a constant learning gain.

5. If $\|\boldsymbol{\theta}_{i+1} - \boldsymbol{\theta}_i\|$ is not too large, go to the next step; else, go back to 1..

6. If the termination criterion are not met, set $i = i + 1$ and go to 1.; else terminate the parameter learning process.

The whole parameter learning process is described by a flow chart as given in Fig. 7.2. Two important conditions on a_i and c_i must be satisfied to guarantee asymptotic convergence of $\boldsymbol{\theta}$ to the optimal parameter, which are summarized as:

1. $a_i > 0$, $a_i \to 0$ as $i \to 0$, and $\sum_{i=0}^{\infty} a_i = \infty$,

2. $c_i > 0$, $c_i \to 0$ as $i \to 0$, and $\sum_{i=0}^{\infty} (\frac{a_i}{c_i})^2 < \infty$.

In practice, exponentially decreasing a_i and c_i are used, i.e. $a_i = \frac{a_0}{(i+1+A)^{\alpha}}$ and $c_i = \frac{c_0}{(i+A)^{\gamma}}$, where A is a positive integer, a_0 and c_0 are positive constants, α and γ are positive constants.

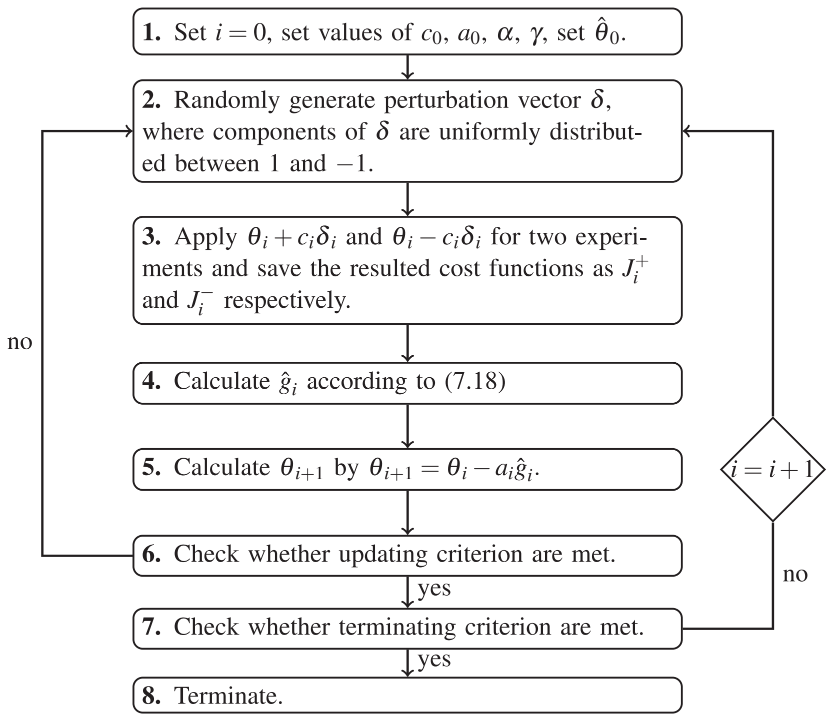


Fig. 7.2: The diagram of *SPSA* based parameter learning algorithm for tuning desired mainstream densities.

7.4 Illustrative Example

7.4.1 Simulation Setup

To validate the proposed method, a freeway network shown in Fig. 7.3 is considered. The freeway network is comprised of 10 mainstream sections, 2 on-ramp links, and 1 off-ramp link is considered. All mainstream sections have 3 lanes and all on-ramp and off-ramp links have a single lane. The two on-ramp links are connected with section 4 and 8 at the beginning location, the off-ramp link is connected with section 5 at the ending position. *METANET* model is used to simulate the freeway system, and model parameters are listed in Tab. 7.1. The traffic demand profiles are given in Fig. 7.4.

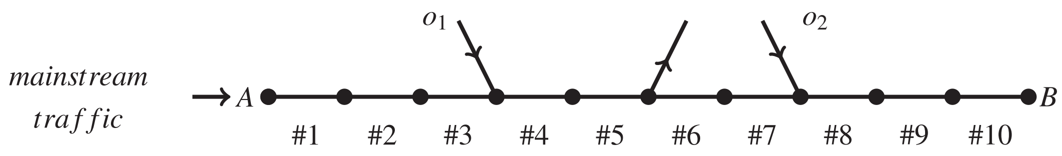


Fig. 7.3: Layout of the benchmark freeway network model.

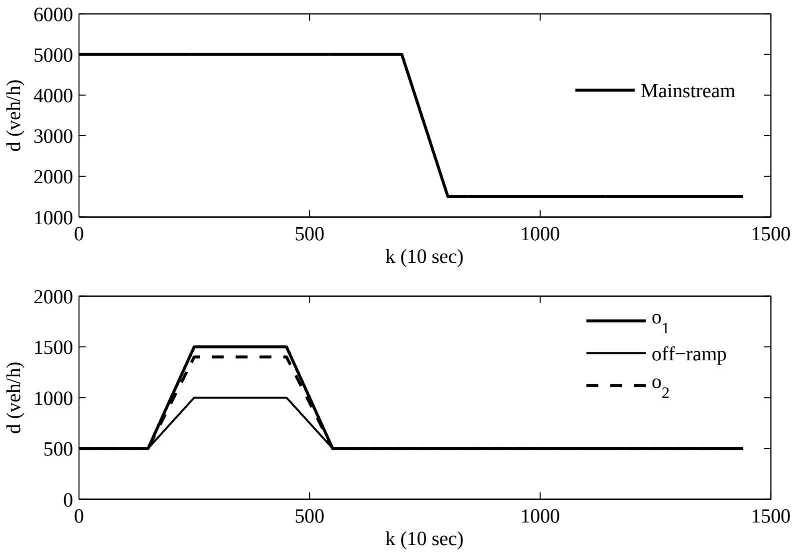


Fig. 7.4: Traffic demand. A total time of 3 hours is considered. A traffic volume at 5000 veh/hour is considered during the peak traffic hours on the freeway mainstream, which drops to 1500 veh/hour at a later time. The traffic demands at the two on-ramp links and the off-ramp link also consider peak hour traffic. Random noise with amplitude 10% of the above demand is imposed in the simulations.

v_f $km/hour$	ρ_c $veh/lane/km$	ρ_{max} $veh/lane/km$	a	μ $km^2/hour$
110	33.5	180	1.636	60
ϕ $veh/lane/km$	β $km/hour$	n_p	planning period $minute$	L km
40	10	24	10	0.5

Tab. 7.1: METANET model parameters.

7.4.2 Case Studies

The following three scenarios are investigated in the numerical studies:

No Control

No ramp metering is applied at on-ramp entries, and vehicles are allowed to merge into the freeway freely.

ALINEA

ALINEA algorithm is applied at all on-ramp entries, and the mainstream density are to be maintained at the critical density value. No constraints is applied to control the queue volumes on the on-ramp links.

ALINEA-Q

ALINEA is applied for ramp metering, and constraints are enforced to prevent formulations of high queue volumes.

MTS

The macroscopic traffic scheduling method is applied for ramp metering. Macroscopic traffic scheduling is utilized to determine the desired mainstream densities for each control period. *ALINEA* is applied at the local ramp metering level to track the predetermined mainstream densities on the freeway mainstream.

MTS-Q

The macroscopic traffic scheduling based ramp metering is implemented with constraints on queue volumes enforced.

In the simulation studies, the learning rate a_i and perturbation amplitude c_i in *SPSA* based parameter learning are defined as:

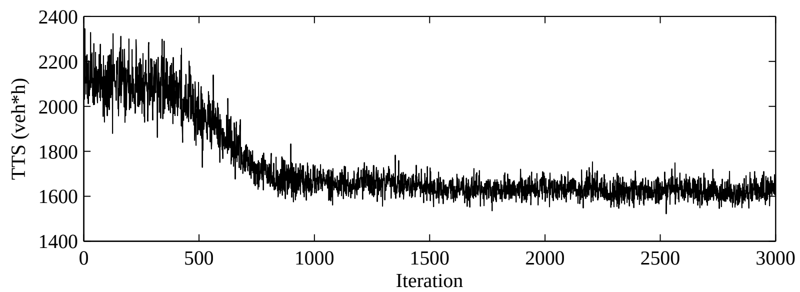
$$a_i = \frac{a_0}{(i+1)^\alpha} \tag{7.19}$$

$$c_i = \frac{c_0}{(i+1)^\gamma}, \tag{7.20}$$

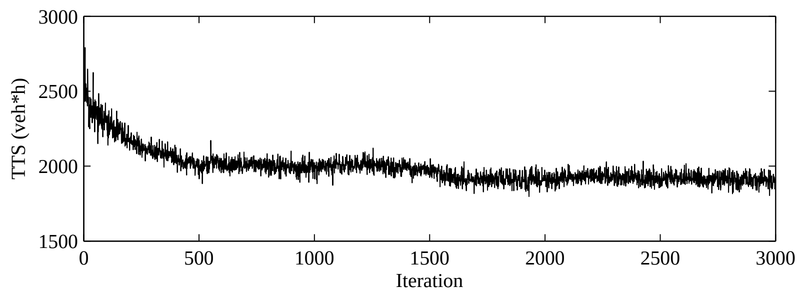
where values of α, γ as suggested by [75] are used, $a_0 = 0.002$ and $c_0[j] = 0.05\rho_c$, $\forall j$.

The reference signals are set as $\rho_{r,\lambda}(p) = \rho_c$, $\forall \lambda$, p in the first iteration. This makes it equivalent to an *ALINEA* based ramp metering algorithm, which guarantees good system performance in the first iteration.

7.4.3 Results and Discussion



(a) Evolution of *TTS* using *MTS*.



(b) Evolution of *TTS* using *MTS-Q* (($\omega_{max} = 250$)).

Fig. 7.5: Evolution of *TTS*.

The evolutions of *TTS* values for 3000 iterations using *MTS* and *MTS-Q* cases are shown in Fig. 7.5. It is clear that by using the proposed *SPSA* based parameter learning approach, the TTS value is significantly reduced in both cases, indicating that the efficiencies of networked ramp metering is greatly improved in both cases. The initial TTS value in MTS and MTS-Q cases are around 2100 and 2500 $veh \cdot h$ respectively. The minimum TTS values, around 1600 and 1900 $veh \cdot h$, are reached after 1500 and 750 iterations in MTS and MTS-Q cases respectively. The reduction in TTS are 23.8% and 24.0% in MTS and MTS-Q case respectively, which means considerably improved freeway traffic conditions in both cases are obtained.

Note that the initial and minimum TTS values in MTS-Q case are increased by 19.0% and 18.8% compared with those in MTS case, which is due to the implementation of queue constraints in MTS-Q case.

It is also worth noting that the evolution of TTS is fluctuated. This is due to the randomness in the freeway process, for example, randomized freeway demand, and such randomness will result in variations in the performance of the same ramp metering strategy. It should be mentioned that such randomness are important features of freeway traffic systems, and it also makes the optimal ramp metering problem more challenging. However, the impact of the freeway system randomness to the performance of freeway ramp metering have never been discussed by existing studies.

The density profiles at on-ramp connected mainstream sections are shown in Fig. 7.6 and Fig. 7.7, the profiles of queue volumes at on-ramp links are shown in Fig. 7.8 to Fig. 7.9. From these results, the following interesting findings are summarized:

- By merging almost all vehicles from the on-ramp links without ramp metering, the mainstream traffic is highly congested.

- By driving the mainstream density to track the critical density, *ALINEA* based ramp metering effectively prevented the occurrence of mainstream congestions.

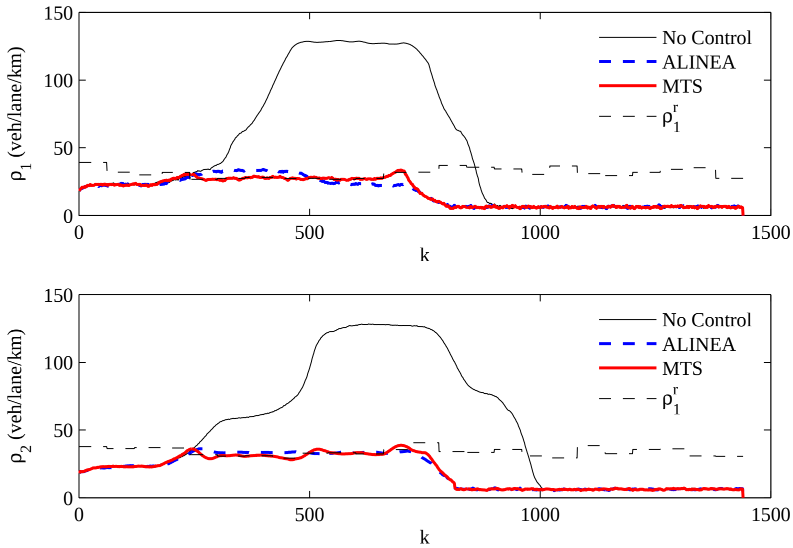


Fig. 7.6: Mainstream density profile using MTS. ρ_1^r and ρ_2^r are the scheduled mainstream density valued at on-ramp link 1 and 2. *No-Control*: Without ramp metering, mainstream congestions occur on the mainstream around both on-ramp links during the time intervals from 250 to 750 (which will be referred as the congestion period in the following). *ALINEA*: Under *ALINEA* control, mainstream congestions are prevented, and the mainstream densities around both on-ramp connected locations are maintained at the critical density during the congestion period in no-control case, except that mainstream density around on-ramp 1 drops below the critical density due to the unavailability of enough on-ramp traffic. *MTS*: Using *MTS* without queue constraint, the mainstream densities at on-ramp 1 is kept below the critical density throughout the congestion period. mainstream density at on-ramp 2 is kept slightly below the critical density during the initial part of the congestion period and slightly above the critical density during a later part of the congestion period. The mainstream densities around both on-ramp links tracks the scheduled mainstream densities closely during the congestion period. During the rest of the time, mainstream densities are obviously lower than the scheduled values.

However, large queue volume, over 600 vehicles, is created at the on-ramp link 2. *ALINEA-Q* based ramp metering effectively prevented the formulation of high queue volumes on the on-ramp links. However, mainstream density increases significantly, especially around on-ramp link 1.

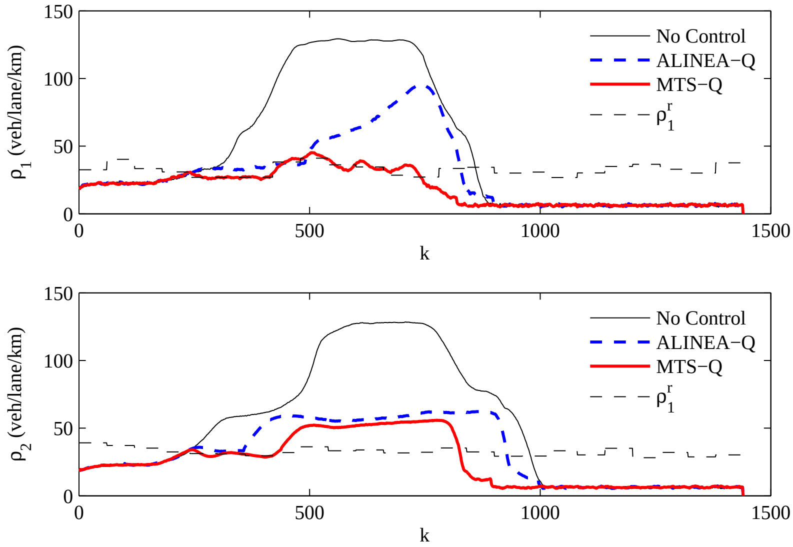


Fig. 7.7: Mainstream density profile using *MTS-Q* (ω_{max} = 250). *ALINEA-Q*: With *ALINEA-Q* based ramp metering, congestion on the freeway mainstream are mitigated. Mainstream densities around both on-ramp links increase considerably above the critical density, especially around on-ramp 1. *MTS-Q*: With *MTS-Q* based ramp metering, mainstream density around on-ramp 1 follows the scheduled mainstream density closely during the congestion period. Mainstream density around on-ramp 2 tracks the scheduled mainstream density during the initial time of the congestion period, but increases considerably above the scheduled values during the rest time of the congestion period.

- Without queue constraints, the *MTS* based ramp metering have achieved macroscopic redistribution of freeway traffic in the time domain, i.e. vehicles merged at the on-ramp link 1 is reduced to allow the creation of moderate queue volume so that more vehicles at on-ramp link 2 is merged and the queue volume there is greatly reduced.

- Implementation of queue constraint does not guarantee the optimal performance of ramp metering, although queue volumes can be effectively restricted. However, by restricting the on-ramp queue volume, the ramp metering strategy will be fairer to vehicles from the on-ramp link, i.e. vehicles from the on-ramp link are not forced to queue and wait in order to achieve the optimal network performance.

- When *MTS* is used, the scheduled mainstream densities are closely tracked on the freeway mainstream during the congestion periods. The scheduled values are higher than the actual mainstream densities, because the traffic demand during the rest of time are insufficient to maintain the scheduled mainstream densities.

- When queue constraint is applied, variations in the merging flow and mainstream densities will occur, which is unfavorable in real systems due to the violent fluctuations in the control signal and traffic flow states.

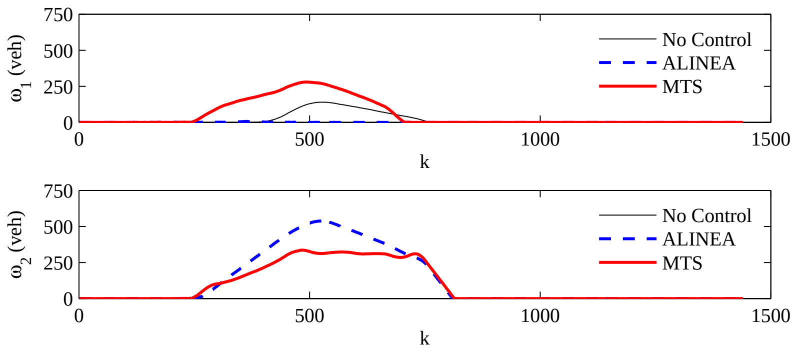


Fig. 7.8: Volumes of queueing vehicles at on-ramp links without queue constraint. *No Control*: Nearly all vehicles from the on-ramp links are merged except that a small queue volume occurs around $k = 500$ at on-ramp 1. *ALINEA*: Large volumes of queuing vehicles occurs at on-ramp 2 during $k = 250$ to $k = 800$. There is only a minor amount of queueing vehicles at on-ramp 1. *MTS*: Large volume of queue is created at on-ramp 1 and the queue volume is significantly higher than that in no control case and ALINEA case. A maximum queue volume of about 300 vehicles occurs at $k = 500$. At on-ramp 2, the queue volume is considerably reduced compared with that of ALINEA case. The maximum queue volume is about 300 vehicles.

Since the performance of *MTS-Q* suffers from the implementation of queue constraints, it is interesting to investigate the effect of different queue constraints on performance of *MTS-Q* based ramp metering. Evolutions of *TTS* using *MTS-Q* based ramp

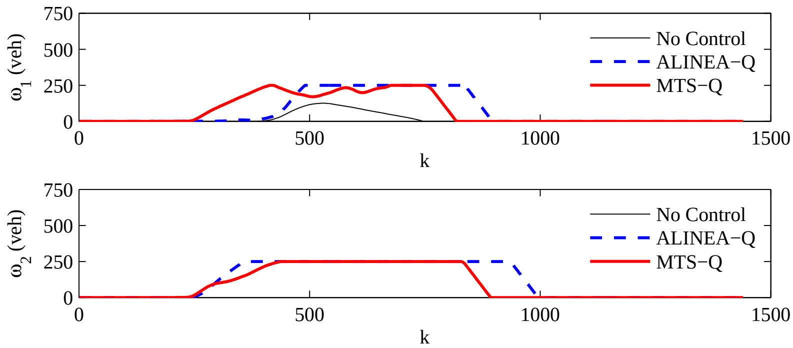


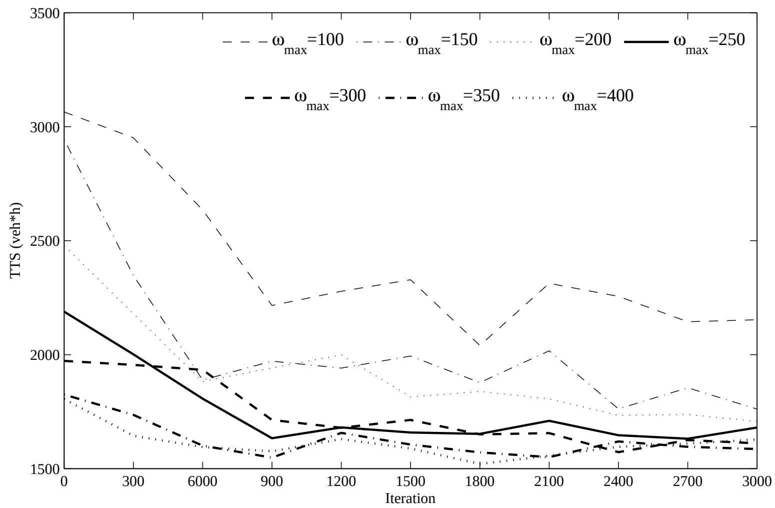
Fig. 7.9: Volumes of queueing vehicles at on-ramp links with queue constraint ($\omega_{max} = 250$). *ALINEA-Q*: Queue volumes at both on-ramp links are capped by the constraint values (250 vehicles) during the congestion period. *MTS-Q*: The queue volume at on-ramp 1 occurs at an earlier time compared with that of *ALINEA* case and a reduction of queue volume occurs during the congestion period. At on-ramp 2, the on-ramp queue starts at a later time and ends earlier compared with that of ALINEA-Q case.

metering with varied ω_{max} values are given in Fig. 7.10. From these results, the following can be concluded:

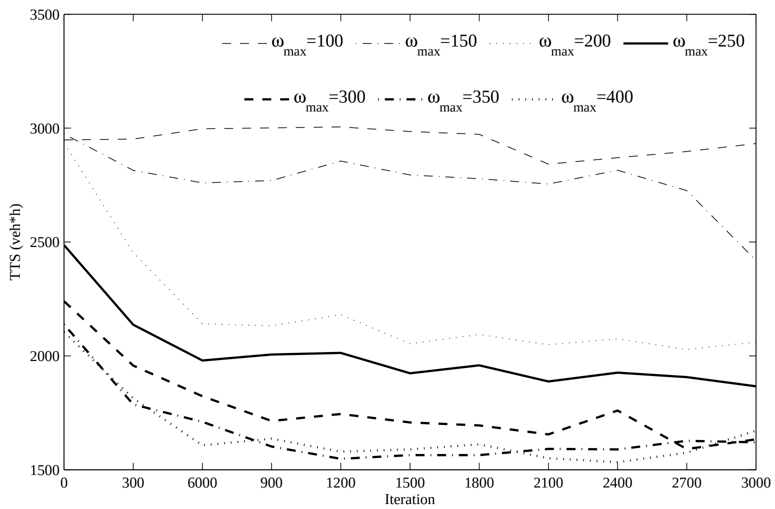
- When larger ω_{max} is used, better optimal performances are obtained by both *MTS* and *MTS-Q* based ramp metering.

- The *TTS* values of *MTS-Q* based ramp metering are consistently higher than those of *MTS* cases.

- The influences of ω_{max} to performances of *MTS* and *MTS-Q* based ramp metering are insignificant when large ω_{max} values is used, i.e. $\omega_{max} > 300$. This can be straightforwardly explained by the fact that when ω_{max} is larger than the maximum possible queue volume when no queue constraint is applied, queue constraint will be ineffective and unnecessary.



(a) Evolution of TTS using MTS.



(b) Evolution of TTS using MTS-Q.

Fig. 7.10: Evolution of TTS under varied queue constraints. Without queue constraint, the minimum TTS values of obtained by MTS based ramp metering decreases as ω_{max} is increased, indicating improved performance of ramp metering. The reduction in the optimal TTS values is insignificant when $\omega_{max} > 250$. With queue constraint implemented, the minimum TTS values achieved by MTS-Q based ramp metering also decreases when ω_{max} is increased, and this reduction is insignificant when larger ω_{max} value is used.

7.4.4 Further Discussion

Investigation on different lengths of period

Note that n_p can also be regarded as a decision variable for the macroscopic scheduling problem. A larger n_p allows more detailed scheduling, but increases the number of variables to be scheduled and complexity of the problem at the meantime. A smaller n_p reduces the number of variables to be determined and makes the traffic control less sensitive to temporal variations in the traffic conditions. When $n_p = K$, the reference mainstream density needs to be scheduled for each time interval, macroscopic traffic scheduling is transformed back into a pure fixed time strategy. When $n_p = 1$, a constant reference mainstream density is used, and ramp metering becomes a reference tracking problem. *ALINEA* falls into this case, where the reference mainstream density is set as the critical density. When $1 < n_p < K$, the problem is transformed into a macroscopic scheduling problem and the reference signals are updated less frequently than that in pure fixed time strategy and more frequently than that in *ALINEA* case.

To investigate the performance of the proposed method with different lengths of scheduling period, additional case studies are conducted, where different n_p values are used. The investigated scenarios are summarized in Tab. 7.2. Note that scenarios A is an extreme situations, where the most ambitious and detailed scheduling is targeted, which is a similar as the fixed-time strategy.

Fig. 7.11 shows the evolutions of the *TTS* in the studied scenarios. In scenario A, *TTS* is not reduced by the parameter learning scheme. This is probably because the freeway traffic demand is highly random at the microscopic level. (Note that gaussian random noise is applied in the traffic demand.)

In all the other scenarios, *TTS* values are reduced during the repeated parameter

Tab. 7.2: Scenarios with different n_p.

Scenario	n_p	Planning Period
A	1440	10 seconds
B	240	1 minute
C	48	5 minutes
D	24	10 minutes
E	8	30 minutes

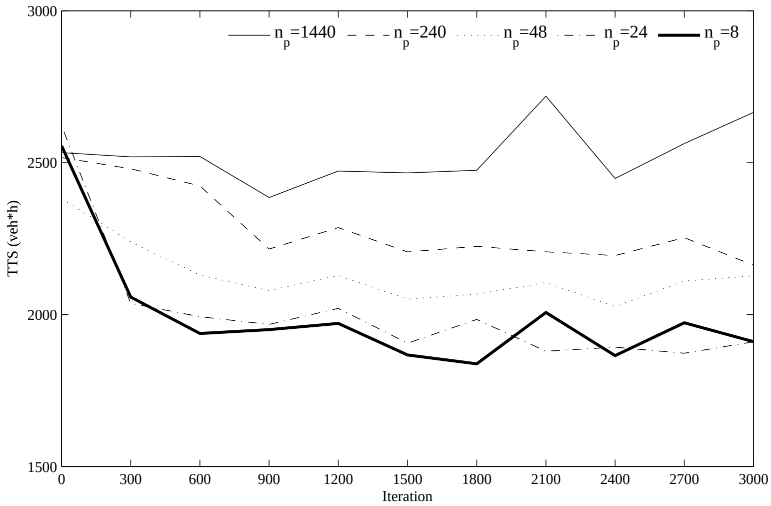


Fig. 7.11: Evolution of TTS using different n_p.

learning process. And it is worth mentioning that when n_p is decreased, lower TTS values are achieved. This shows that the performance of MTS strategy based ramp metering approach improves as the length of the planning period is increased. This phenomenon illustrates that when the length of the planning period is increased, the macroscopic level freeway traffic repetitiveness can be utilized better by the MTS strategy.

Furthermore, the final TTS values obtained in scenarios D and E are comparable. It shows that the MTS strategy has been quite effective with the corresponding values of n_p.

Communication Cost

To realize the proposed parameter learning scheme in real implementations, communication is needed between the local controllers and a control center. For instance, local controllers must report local traffic conditions to the the control center so that TTS can be calculated after a complete freeway operation trial, and updated reference signals must be transmitted to local controllers before the next freeway operation trial. The existence of the control center and the communication mechanism makes the proposed algorithm a centralized control method. However, it is worth mentioning that once reference signals are determined and transmitted to the local controllers, no further communication is needed during the whole period of freeway operation. Hence the communication cost required by the proposed method is very low compared with that of MPC based methods, where regular communication is a must between the control center and local controllers.

Implementation Issue

Freeway traffic load during mid-night time, i.e. from 11:00 PM to 3 AM, is very low, therefore, no ramp metering is needed during this period. Therefore, the communication activities and parameter updating tasks can be carried out during this period. By this arrange of communication activities and parameter updating tasks, normal freeway operation is uninterrupted. The above feature makes the proposed method especially suitable for real implementations, because improved system performance is obtained through day-to-day parameter learning without any interference to normal freeway operations.

7.5 Conclusions

To solve the networked freeway ramp metering problem, a novel macroscopic freeway traffic scheduling method is proposed, which combines a macroscopic traffic scheduling approach with the *ALINEA* based traffic responsive ramp metering strategy. At the macroscopic level, time and location specific reference mainstream density signals are scheduled, where the macroscopic repetitiveness in freeway traffic is utilized. While at the microscopic level, the *ALINEA* based traffic responsive local ramp metering algorithm is applied to maintain the local mainstream densities at the corresponding reference values. The *ALINEA* based reference tracking scheme enables the traffic scheduling method to cope with the randomness and variations in freeway traffic. By the proposed method, the networked freeway ramp metering problem is simplified as an optimization problem, where the reference signals are the decision variables. To find the optimal macroscopic traffic scheduling plan, which results in minimum *TTS*, an *SPSA* based parameter learning algorithm is used to tune the reference signals. The combined use of macroscopic traffic scheduling and *ALINEA* effectively improves the efficiency of networked ramp metering system, while the advantages of both methods, i.e. the structural simplicity of the macroscopic traffic scheduling approach, and the capability of *ALINEA* to cope with real time traffic situations, are retained. As a centralized control approach, the proposed method requires minor communication cost and is suitable for real implementation, because no interruption to normal freeway operation is incurred. Case studies show that the proposed method greatly improves the performance of networked freeway ramp metering systems. The proposed method achieves minimum *TTS* that is 23.8% lower than that of *ALINEA* case when no queue constraint is not applied, and 24% lower than that of *ALINEA* case when queue constraint is applied.

In this chapter, the ramp metering control problem for networked freeway traffic is solved by combining the ALINEA control algorithm with an SPSA based parameter learning algorithm. By the proposed approach, macroscopic repetitiveness of freeway traffic is considered and utilized to formulate the original problem as a macroscopic traffic planning problem. The mainstream traffic densities around controlled on-ramp entries are maintained at desired values during specified time periods. The ALINEA based local ramp metering law is adopted to maintain the mainstream densities at the corresponding desired values. In order to obtain the optimal system performance, the SPSA based parameter learning algorithm is adopted for tuning the desired mainstream mainstream density values. The proposed approach pursues macroscopic optimality of the network-wide freeway traffic flow while retaining the simplicity of ALINEA and fixed time control strategy; additionally, the computational power for real implementation is less demanding than existing algorithms.

Chapter 8

Conclusions

8.1 Summary of Results

In this thesis, the learning based parameter calibration and ramp metering problems were studied for the freeway traffic system, several innovative algorithms were proposed, which complement existing studies and address the limitations of existing methods.

In particular, the problem of parameter calibration for macroscopic freeway traffic modeling is studied in Chapter 3, where a novel hybrid iterative calibration algorithm was proposed. The hybrid algorithm adopts multiple MSE based cost functions to measure the discrepancies between model generated data sets and real traffic data sets. By combining the multivariate Newton-Raphson algorithm with the simultaneous perturbation based gradient estimation, the proposed hybrid iterative algorithm aims at finding the optimal parameters to minimize all cost functions. The gradient estimation scheme avoided the involvement of complex model based gradient calculation, while parametric convergence is theoretically guaranteed by virtue of the multivariate Newton-Raphson algorithm. Besides, randomness is introduced into the parameter updating process to enhance the quality of parametric convergence in face of local minima. In simulation studies with real freeway data, the proposed method effectively calibrates the METANET model parameters to obtain excellent fitting between model generated data and real data, and the MSE values with respect to multiple data sets are significantly lower than that obtained by the SPSA based parameter calibration. This part of the work demonstrates that the proposed hybrid iterative calibration algorithm is an effective and useful alternative to existing parameter calibration methods.

In Chapters 4 and 5, the problem of optimal freeway local ramp metering is considered, where the main objective is to strike a balance between mainstream and on-ramp traffic conditions while pursuing the optimal performance of local ramp metering systems. A WTTS based cost function is adopted to measure the efficiency of freeway local ramp metering, and a balance between mainstream and on-ramp traffic is essentially pursued by the WTTS based cost function. Additionally, WTTS based cost function requires less implementation cost compared with that of TTS based cost function. FLC based local ramp metering algorithms are proposed to determine the reference mainstream density based on traffic conditions on the freeway mainstream and on-ramp link. The local feedback control based algorithm is then used maintaining the mainstream traffic density around the reference density. To find the optimal parameter settings for the FLC based local ramp metering algorithms, two parameter tuning schemes are proposed.

Specifically, in Chapter 4, repeated freeway traffic demands with system randomness are considered, and PARAMICS microscopic traffic simulation is used to evaluate the performance of the ramp metering algorithm. Antecedent membership functions in the FLC algorithm is predefined and consequent parameters are regarded as tunable parameters. The PSO algorithm is used to find the optimal parameters that minimizes the WTTS value. Simulation results show that the proposed method effectively finds the optimal ramp metering policies to strike a balance between freeway mainstream and on-ramp traffic.

Another parameter tuning scheme is proposed in Chapter 5 to find the optimal settings of the FLC based local ramp metering algorithm. Different from the previous chapter, time space variations in traffic demands are considered in this chapter and parameters in both the antecedent and consequent parts of the FLC algorithm are considered as tunable parameters. These parameters are tuned using an SPSA based model-free parameter learning algorithm, which iteratively learns from operation trials with perturbed system parameters to update the parameters and improve system performance. A desirable feature of the SPSA based parameter learning scheme is that the normal freeway operation is uninterrupted by the parameter learning. Case studies using METANET model show that the new parameter tuning scheme can effectively find the optimal parameters of the FLC algorithm and obtain a balance between mainstream traffic and on-ramp traffic. Furthermore, the performance of the proposed method is able to cope with various randomness in freeway traffic demands and suitable for realtime implementations.

In Chapters 6 and 7, the networked freeway ramp metering problem is studied, where simultaneous control of multiple on-ramp links is considered. It is a more challenging problem due to the complex interactions among local controllers, on which no explicit relationship has been established, however, to obtain the optimal system performance, the behaviors of these local controllers should be properly coordinated. Traditional centralized control based coordinated ramp metering systems are limited by the involvement of complex model based calculation, low system flexibility and high computation cost. To address these drawbacks of existing methods, two new centralized control based ramp metering strategies are proposed, which are simple, efficient and suitable for realtime implementations.

Firstly, a novel local coordinative ramp metering strategy is proposed, by which local controllers exchanged their measurement information with neighboring controllers. Based on both local and exchanged traffic measurements, FLC based coordinative decision making algorithms are used by local controllers to coordinately make decisions on the reference mainstream densities, which are tracked using feedback control based algorithm. The parameters of the FLC based coordinative decision making algorithms are iteratively updated using an SPSA based parameter learning scheme. By the proposed local coordinative ramp metering strategy, local controllers communicate with their neighboring controllers rather than continuous communications with the control center, hence communication cost is reduced. Furthermore, the no complex model based calculation is involved by the proposed algorithm, therefore, simple algorithmic structure is obtained. Efficiency of the proposed strategy is demonstrated through extensive case studies, where TTS is significantly reduced compared with that of uncoordinated feedback control based ramp metering case.

Finally, another macroscopic traffic scheduling strategy is proposed for networked freeway ramp metering. This novel ramp metering strategy considers the freeway traffic as a macroscopically repeated process, where reference mainstream densities are scheduled for predefined time periods. These reference signals are tracked accordingly by local controllers using feedback control based algorithm. By the proposed macroscopic traffic scheduling strategy, the networked ramp metering problems is simplified as a optimization problem, where the time and location specific reference signals are treated as decision variables. A model-free SPSA based parameter learning algorithm is used to iteratively update these scheduled reference signals and improve the system performance. The proposed strategy requires minor communication cost in addition to the implementation cost of uncoordinated feedback control based ramp metering strategy. Besides, the structure of the proposed strategy based ramp metering system is quite simple. These important characteristics of the proposed strategy together with its significantly improved efficiency compared with that of the local feedback control based strategy make it suitable for realtime implementations.

Additionally, traffic data collected from real traffic systems is used for calibrating the parameters of the macroscopic traffic flow models. This adds up to the importance of the research in this thesis for solving real and practical problems.

Meanwhile, popular traffic flow models are applied for simulating the freeway traffic flow, where various practical issues in real freeway systems are carefully considered, e.g. randomness and variations in freeway traffic demands, freeway congestions. In particular, the well-known METANET model is used to simulate freeway traffic flow for both local and coordinated freeway ramp metering problems, and the PARAMICS microscopic traffic simulation platform is used, which enables the performance of ramp metering algorithms to be investigated under traffic situations that is close to real traffic situations.

Overall, several important issues in freeway traffic modeling and control are investigated and successfully addressed. Achievements obtained mainly lie in:

1. improving the accuracy parameter calibration for freeway traffic modeling,
2. improving the efficiency of both local and networked freeway ramp metering,
3. handling freeway system randomness and uncertainties,
4. realizing model-free parameter learning to adjust parameters of the control algorithms without interrupting normal freeway operation,

5. exploring the potentials of existing methodologies to obtain simple but more efficient freeway ramp metering algorithms,

6. utilizing both macroscopic and microscopic traffic simulations to facilitate effective design and analysis of freeway ramp metering systems,

where the current work can serve as good reference.

8.2 Suggestions for Future Work

It would be desirable that future research could be done to improve the current study in the following aspects:

1. In this thesis, freeway traffic control is realized by ramp metering, however, variable speed limit control based strategies also worth consideration. It can be used jointly with ramp metering to improve the efficiency of freeway traffic control systems.

2. Real traffic data used for numerical studies in this thesis is limited due to limited resources available, otherwise, the proposed methods can be further validated against more complex freeway networks and real traffic data.

3. Field testing with the proposed ramp metering strategies would be of substantial importance to demonstrate their efficiencies.

4. The proposed ramp metering schemes mainly focus on improvement of ramp metering performances. Further studies are needed to provide theoretical basis for the various algorithms proposed in this thesis.

The above mentioned issues suggest interesting topics for future studies, for which this thesis can serve as a starting point and reference.

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Appendix A: Proof Details

A.1 Proof of *Theorem 1*

Proof. At each iteration, by the mean value theorem and Taylor's expansion, we have

$$d\boldsymbol{L}_i = J\left(\bar{\boldsymbol{\theta}}_{i_1}\right) d\boldsymbol{\theta}_i, \tag{8.1}$$

and

$$\delta\boldsymbol{L}_i = J\left(\bar{\boldsymbol{\theta}}_{i_2}\right) \delta\boldsymbol{\theta}_i, \tag{8.2}$$

where $\bar{\boldsymbol{\theta}}_{i_1}$ denotes a point on the line segment of $\hat{\boldsymbol{\theta}}_i$ and $\hat{\boldsymbol{\theta}}_i + d\boldsymbol{\theta}_i$, $\bar{\boldsymbol{\theta}}_{i_2}$ denotes a point on the line segment of $\boldsymbol{\theta}_*$ and $\hat{\boldsymbol{\theta}}_i$.

Let J_{i_1} and J_{i_2} denote $J\left(\bar{\boldsymbol{\theta}}_{i_1}\right)$ and $J\left(\bar{\boldsymbol{\theta}}_{i_2}\right)$ respectively. The evolution of cost functions during the parameter calibration process is expressed as:

$$\begin{aligned}
\boldsymbol{L}_{i+1} &= \boldsymbol{L}_i + d\boldsymbol{L}_i \\
&= \boldsymbol{L}_i + J_{i_1} d\boldsymbol{\theta}_i \\
&= \boldsymbol{L}_i - a_i J_{i_1} \hat{J}_i^{-1} \boldsymbol{L}_i.
\end{aligned} \tag{8.3}$$

Using $\boldsymbol{L}_*$ to subtract both sides of the above relationship, we have

$$\delta\boldsymbol{L}_{i+1} = (I - a_i J_{i_1} \hat{J}_i^{-1})\delta\boldsymbol{L}_i + a_i J_{i_1} \hat{J}_i^{-1} \boldsymbol{L}_*. \tag{8.4}$$

Let ρ_1 be the upper bound of $\left\| I - a_i J_{i_1} \hat{J}_i^{-1} \right\|$, and ϵ_1 be the upper bound of $\left\| a_i J_{i_1} \hat{J}_i^{-1} \boldsymbol{L}_* \right\|$, apply norm on both sides of the relationship (8.4), we have

$$\begin{aligned}
\|\delta \boldsymbol{L}_{i+1}\| &= \left\|(I - a_i J_{i_1} \hat{J}_i^{-1})\delta \boldsymbol{L}_i + a_i J_{i_1} \hat{J}_i^{-1} \boldsymbol{L}_*\right\| \\
&\le \left\|I - a_i J_{i_1} \hat{J}_i^{-1}\right\| \|\delta \boldsymbol{L}_i\| + \left\|a_i J_{i_1} \hat{J}_i^{-1} \boldsymbol{L}_*\right\| \\
&\le \rho_1 \|\delta \boldsymbol{L}_i\| + \epsilon_1 \\
&\le \rho_1^{i+1} \|\boldsymbol{L}_0\| + \epsilon_1 \sum_{j=0}^{i} {\rho_1}^j \\
&= \rho_1^{i+1} \|\boldsymbol{L}_0\| + \epsilon_1 \frac{1 - {\rho_1}^{i+1}}{1 - \rho_1} \qquad (8.5)
\end{aligned}$$

hence if $\rho < 1$, we have

$$\lim_{i \to \infty} \|\delta \boldsymbol{L}_i\| = \frac{\epsilon_1}{1 - \rho_1}, \qquad (8.6)$$

which means $\boldsymbol{\theta}_i$ converges to a bounded neighborhood of $\boldsymbol{\theta}_*$. Since ϵ_1 depends on a_i, the radius of the bounded neighborhood can be reduced by adopting a smaller updating gain.

By proper gradient estimation method, e.g. simultaneous perturbation algorithm, we are able to obtain estimated Jacobian matrix such that $J_{i_1} \simeq J\left(\hat{\boldsymbol{\theta}}_i\right)$. By adopting a small enough updating rate which makes $\bar{\boldsymbol{\theta}}_{i_1}$ and $\hat{\boldsymbol{\theta}}_i$ close enough to each other, we obtain $\left\|I - a_i J_{i_1} \hat{J}_i^{-1}\right\| \le \rho_1 < 1$, satisfying the convergence criteria for $\delta \boldsymbol{L}_i$.

Since

$$\hat{\boldsymbol{\theta}}_{i+1} = \hat{\boldsymbol{\theta}}_i - a_i \hat{J}_i^{-1} \boldsymbol{L}_i, \qquad (8.7)$$

using $\boldsymbol{\theta}_*$ to subtract both sides of the above relationship, we have

$$\boldsymbol{\theta}_* - \hat{\boldsymbol{\theta}}_{i+1} = \boldsymbol{\theta}_* - \hat{\boldsymbol{\theta}}_i + a_i \hat{J}_i^{-1} \boldsymbol{L}_i \qquad (8.8)$$

hence, we have

$$\begin{aligned}\delta\boldsymbol{\theta}_{i+1} &= \delta\boldsymbol{\theta}_i + a_i\hat{J}_i^{-1}(\boldsymbol{L}_i - \boldsymbol{L}_* + \boldsymbol{L}_*),\\ &= \delta\boldsymbol{\theta}_i - a_i\hat{J}_i^{-1}\delta\boldsymbol{L}_i + a_i\hat{J}_i^{-1}\boldsymbol{L}_*\\ &= \delta\boldsymbol{\theta}_i - a_i\hat{J}_i^{-1}J_{i_2}\delta\boldsymbol{\theta}_i + a_i\hat{J}_i^{-1}\boldsymbol{L}_*\\ &= (I - a_i\hat{J}_i^{-1}J_{i_2})\delta\boldsymbol{\theta}_i + a_i\hat{J}_i^{-1}\boldsymbol{L}_* \end{aligned} \tag{8.9}$$

Apply norm on both sides of the above relationship, we have

$$\begin{aligned}\|\delta\boldsymbol{\theta}_{i+1}\| &= \|(I - a_i\hat{J}_i^{-1}J_{i_2})\delta\boldsymbol{\theta}_i + a_i\hat{J}_i^{-1}\boldsymbol{L}_*\|\\ &\le \|(I - a_i\hat{J}_i^{-1}J_{i_2})\delta\boldsymbol{\theta}_i\| + \|a_i\hat{J}_i^{-1}\boldsymbol{L}_*\|\\ &= \|(I - a_i\hat{J}_i^{-1}J_{i_2})\|\|\delta\boldsymbol{\theta}_i\| + \|a_i\hat{J}_i^{-1}\boldsymbol{L}_*\| \end{aligned} \tag{8.10}$$

Let ρ_2 denote the upper bound of $\|I - a_i\hat{J}_i^{-1}J_{i_2}\|$, ϵ_2 denote the upper bound of $\|a_i\hat{J}_i^{-1}\boldsymbol{L}_*\|$, we have

$$\begin{aligned}\|\delta\boldsymbol{\theta}_{i+1}\| &\le \rho_2\|\delta\boldsymbol{\theta}_i\| + \epsilon_2\\ &\le {\rho_2}^{i+1}\|\delta\boldsymbol{\theta}_0\| + \epsilon_2\sum_{j=0}^{i}{\rho_2}^j\\ &= {\rho_2}^{i+1}\|\delta\boldsymbol{\theta}_0\| + \epsilon_2\frac{1-{\rho_2}^{i+1}}{1-\rho_2}. \end{aligned} \tag{8.11}$$

From the above relationship, it is clear that if $\rho_2 < 1$, we get

$$\lim_{i\to\infty}\|\delta\boldsymbol{\theta}_i\| = \frac{\epsilon_2}{1-\rho_2}, \tag{8.12}$$

indicating that $\boldsymbol{\theta}_i$ converges to a bounded neighborhood of $\boldsymbol{\theta}_*$. Similar to the convergence of $\delta\boldsymbol{L}_i$, the radius of this neighborhood can also be reduced by using a small updating gain. □

Appendix B: Published/Submitted Papers

Refereed Journal Articles:

[1] Xu, J.; Zhao, X.; Srinivasan, D., "On optimal freeway local ramp metering using fuzzy logic control with particle swarm optimisation," *Intelligent Transport Systems, IET* , vol.7, no.1, pp.95,104, March 2013.

[2] Xinjie Zhao, Jian-Xin Xu, and Dipti Srinivasan, "A Novel and Efficient Local Coordinative Freeway Ramp Metering Strategy with SPSA based Parameter Learning", Minor Revision (Revision Submitted), *Intelligent Transport Systems, IET.*

[3] Jian-Xin Xu, Xinjie Zhao and Dipti Srinivasan, "A Hybrid Iterative Parameter Estimation Approach for Macroscopic Freeway Traffic Modeling", In Revision, *Transactions on Intelligent Transportation Systems, IEEE.*

[4] Xinjie Zhao, Jian-Xin Xu, and Dipti Srinivasan, "FLC based Adaptive Freeway Local Ramp Metering with SPSA based Parameter Learning", Submitted, *Journal of Intelligent Transportation Systems, JITS.*

[5] Xinjie Zhao, Jian-Xin Xu, and Dipti Srinivasan, "Networked Freeway Ramp Metering Using Macroscopic Traffic Scheduling and SPSA based Parameter Learning", Submitted,

Systems Journal, IEEE.

International Conference Articles:

[1] Jianxin Xu, Xinjie Zhao, and Dipti Srinivasan, "Flow based local ramp metering using iterative learning and PARAMICS platform", in *2009 IEEE International Conference on Control and Automation*, Piscataway, NJ, USA, 2009.

[2] Xinjie Zhao, Dipti Srinivasan, and Jianxin Xu, "Iterative learning control of freeway flow via ramp metering and simulation on PARAMICS", *TENCON 2009 - 2009 IEEE Region 10 Conference*, Singapore, 2009.

[3] Jianxin Xu, Xinjie Zhao, and Dipti, Srinivasan, "Fuzzy logic controller for freeway ramp metering with particle swarm optimization and PARAMICS simulation", *Fuzzy Systems (FUZZ), 2010 IEEE International Conference on*, Barcelona, Spain.

[4] Xinjie Zhao, Jianxin Xu, and Dipti Srinivasan, "Iterative learning control of freeway flow via ramp metering and simulation on PARAMICS", SSCI 2013 - 2013 IEEE Symposium Series on Computational Intelligence, Singapore.