

An integrated framework for adaptive local ramp-metering control

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Abstract

In order to increase the operational capability of transportation systems, nowadays, freeway networks are equipped with ramp-metering systems, which aim to regulate, in an appropriate way, the inflow from on-ramps to the main carriageways. The effectiveness of a ramp-metering system in improving traffic conditions, e.g. by minimizing traffic congestion or journey times, depends highly upon the efficiency of its operational strategy. In this paper we introduce an adaptive framework for local ramp-metering control based on a coupling of the continuum model of traffic flow introduced in [15], [21] with the reinforcement learning approach [23], [25].

1. Introduction

During periods of peak traffic, the introduction of traffic flow from on-ramps to the main carriageway of a freeway network can cause vehicles to change lanes or to brake, which results in flow breakdown on the main carriageway. On the other hand, due to some physical space, financial and environmental constraints, alternatives to address this issue rely often on the optimal exploitation of existing freeway networks' infrastructures. Introduced in the sixties, the ramp-metering concept is a traffic management technique which consists of regulating the flow of additional traffic onto the freeway that, if unregulated would trigger flow breakdown during peak periods. The purpose of a ramp-metering system, see e.g. Figures 1 and 2, is to prevent the onset of flow breakdown on the main carriageway and/or long queue on the ramp, by managing the traffic flow rate entering the main carriageway from the on-ramp. The benefits from installation of ramp-metering systems include greater throughput during peak periods, less congestion, smoother journey times, less fuel consumption, less pollution, reduction of the risk of accidents at on-ramps, etc.

Over the last few decades, ramp-metering control has been an active research area and various algorithms have been suggested to address the problem, see e.g. [6], [12], [13], [16], [17], [18], [19], [22], and the references therein for an overview. Although vehicular traffic is known to be naturally nonlinear and stochastic, most of the ramp-metering models existing in the literature are either static or based on punctual optimization of pre-specified models.

Due to their ability to learn through dynamic interactions with a complex environment, reinforcement learning-based models appear to offer significant advantages compared to traffic control methodologies based on punctual optimization of pre-specified models e.g. [16], [17], [18], [19]. In fact, reinforcement learning could be an effective tool for transportation process management, where real-time control is essential in improving the operational efficiency of traffic systems [1]. Recently, various measures for traffic control have been considered for easing traffic congestion including the development of traffic control models based on reinforcement learning approach e.g. [1], [24]. However, the major shortcoming of these traffic control models is that they are essentially designed for microscopic traffic simulations; hence they are not suitable for handling crowded road networks. In contrast with microscopic models, continuum traffic flow models – also termed macroscopic traffic models –, e.g. [2], [15], [20], [21], describe the overall behavior of the traffic stream rather than the interactions between two individual vehicles, and these models are known to be computationally powerful when simulating traffic flow in crowded road networks. The purpose of this work is to introduce a framework for local ramp-metering

control based on a coupling of the continuum model of traffic flow introduced in [15], [21] with the reinforcement learning approach. A such framework aims to take advantages of both continuum traffic modeling and reinforcement learning approach so as to offer a real potential for an effective traffic control at on-ramps during peak periods.

The remaining part of the paper is organized as follows. Section 2 presents a brief discussion on continuum modeling of vehicular traffic flow and reinforcement learning, respectively. Section 3 introduces the proposed framework and its operational structure. Section 4 presents some numerical simulations on a case study, which illustrate some interesting features of the proposed framework and its potential for real-time applications. Finally, Section 5 concludes the paper and discusses future works.

2. Background

2.1. A brief overview of continuum modelling of traffic flow

Continuum traffic flow models are governed by mass conservation or continuity equation(s) and they are either based on perturbations of the isentropic gas dynamics models or derivation from car-following models e.g. [4], [8]. The first continuum model of vehicular traffic flow has been introduced in the fifties by Lighthill & Whitham [15] and Richards [21], and this model is commonly referred to as the LWR model. The main dependent variables used, in the LWR model, to describe mathematically road traffic dynamics, are the average density $\rho = \rho(x, t)$ and the average velocity $v = v(x, t)$ of cars, respectively at location x and time t . From these quantities another important traffic parameter is derived, namely the traffic flow $q = q(x, t) = \rho v$, which is of great interest for both theoretical and experimental purposes. The LWR model consists of the following single continuity equation:

$$\frac{\partial}{\partial t}\rho(x, t) + \frac{\partial}{\partial x}q(x, t) = 0, \quad (2.1)$$

where, $q(x, t) = \rho(x, t)v(x, t)$. As equation (2.1) involves simultaneously two variables ρ and v , in order to complete the model, closure relation expressing the flow q as a function of the density ρ i.e. of the form $q = f(\rho)$ is commonly devised. A such flow-density relationship is called the fundamental diagram. Let ρ_{max} denotes the maximum density of vehicles allowed along the road, corresponding to a bumper-to-bumper traffic jam. The function f is often required to be: monotonically increasing from $\rho = 0$ up to a certain density value $\sigma \in (0, \rho_{max})$, monotonically decreasing for $\rho \in [\sigma, \rho_{max}]$, and concave with a unique maximum point. The elementary flow-density relationship used in the LWR model [15], [21] is:

$$f(\rho) = \rho v_e(\rho), \quad (2.2)$$

$$\text{where } v_e(\rho) = v_{max} \left(1 - \frac{\rho}{\rho_{max}} \right). \quad (2.3)$$

The parameter $v_{max}(> 0)$ denotes the maximum average velocity, which may be observed by vehicles on an almost empty road.

2.2 A brief overview of the reinforcement learning approach

Reinforcement learning problems encompass problems in which the learner at the same time decision-maker – also called the agent – learns how to act through a direct interaction with the “external world” – also called the environment – in order to achieve a certain goal. Usually, the agent and the environment interact continually, in discrete steps, as follows: At each time step, given a status – also called a state – of the environment the agent performs actions, and as a consequence of these actions the agent receives a reward and the environment presents a new status to the agent. Through this interaction, the goal of the agent is, for each given state of the environment, to select appropriate actions – also called

policy – so as to maximize the total reward it receives during a given time period. The interaction between the agent and the environment is generally hypothesized to satisfy the Markov property, which means that any action of the agent is derived from only the current state of the environment.

3. A scheme for adaptive local ramp-metering control

During the last few decades, the ramp-metering control problem has been an active research area and various heuristics to address the issue have been suggested in the literature, see e.g. [16], [18], [22] for an overview. Current most prominent ramp-metering heuristics are based on approaches including linear programming e.g. [27], nonlinear optimization, e.g. [6], [12], [13], [17], [19], artificial neural networks e.g. [26], [28], reinforcement learning models such as Q-learning e.g. [1] or Sarsa e.g. [24].

Because reinforcement learning approach can handle nonlinear systems with unknown models, it has a distinctive advantage over traditional ramp-metering models, which are only as good as the system model and usually force nonlinear systems into a linear context. However, the major limitation of traffic control models based on reinforcement learning in the literature, e.g. [24], [1], is that they are designed for microscopic traffic simulations. Therefore these models are unusable to handle crowded road networks, thus they are inappropriate for freeway ramp-metering control.

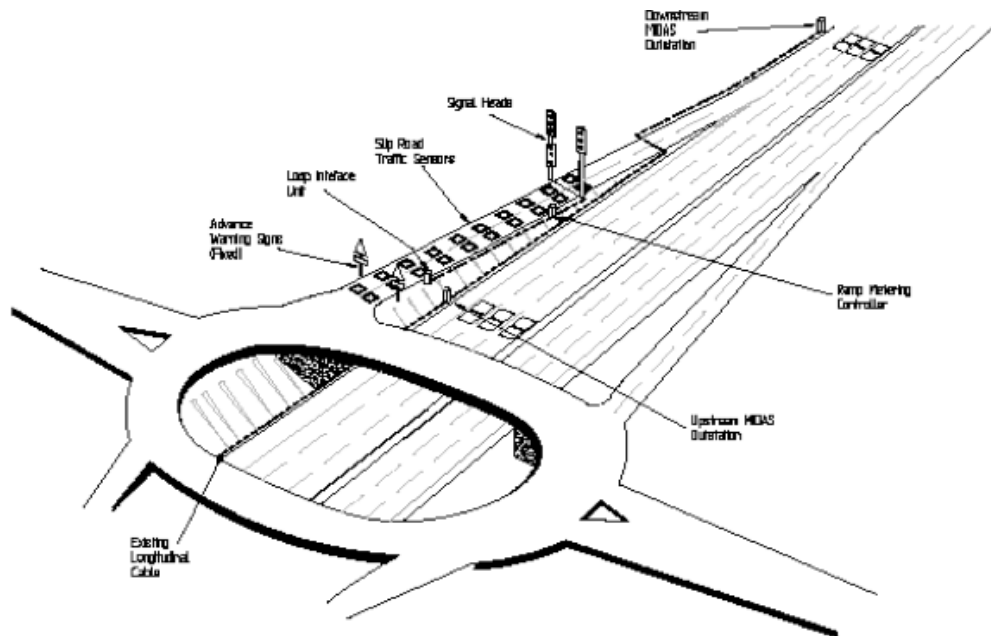


Figure 1. An example of ramp-metering installation.

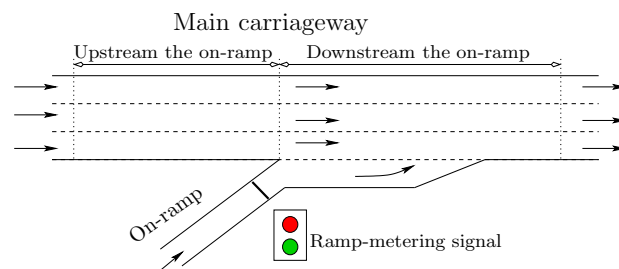


Figure 2. A simplified diagram of an on-ramp equipped with a ramp-metering system.

The aim of this study is to introduce a framework for adaptive local ramp-metering control, which is based on a coupling of reinforcement learning with macroscopic models of traffic flow. The rationale behind this approach is to take advantage of the ability of reinforcement learning to handle nonlinear systems with unknown models on the one hand, and the suitability as well as the computational power of macroscopic models in describing traffic flow, in crowded roads such as freeways, on the other hand.

The ramp-metering problem can be expressed as a reinforcement learning problem in the following way: The state space consists of traffic conditions in the “immediate neighborhood” of the on-ramp, which may include the traffic demand (resp. supply) on the main carriageway upstream (resp. downstream) the on-ramp, the traffic demand on the ramp, the queue length in the ramp, weather conditions, lighting, etc. The set of actions includes: setting to green/red the traffic light at the on-ramp, switching on/off the traffic light at the on-ramp, switching on/off the variable message sign (VMS) on the main carriageway upstream the ramp etc. The agent, i.e. the ramp-metering system, is responsible for:

- interpreting the inputs collected from the environment (e.g. the demand on the main carriageway upstream the ramp, the supply on the main carriageway downstream the ramp, the traffic demand on the ramp, the status of the ramp-metering signal, the status of the variable message signs on the main carriageway, etc.),
- selecting actions on the basis of these inputs, and learning on the basis of the impacts of its actions on the environment. The environment – i.e. the traffic system in the vicinity of the on-ramp – is controlled by actions, which are safe and fair at on-ramps, according to the current traffic conditions on the main carriageway and the on-ramp. Safe and fair actions includes for example actions which minimize risks of collision at the on-ramp as well as the waiting time at the ramp, and such that the queue in the ramp does not exceed the ramp capacity. In this study we consider throughput as the action-value function. Therefore, the agent (i.e. the ramp-metering system) will select safe joint actions according to the current traffic condition so as to maximize the aggregated throughput on the main carriageway downstream the ramp.

An overview of the operational structure of the proposed framework for adaptive local ramp-metering control is presented in Figure 3. More precisely, the framework operates as follows: traffic data are monitored through inductive loops or speed cameras or detectors installed on the main carriageway and on the ramp. These traffic data are used by the ramp-metering system to estimate the best flow rate for the system to operate safely and efficiently so as to maximize the aggregated traffic throughput downstream stream the on-ramp by selecting and coordinating the appropriate actions. Then the estimated flow rate is converted into a period of signal sequences to the road users, in order to dissipate the intended traffic flow rate onto the main carriageway. The proposed framework can be summarized in the following steps:

Step 1: *Collect traffic conditions in the controlled area, i.e. in the vicinity of the on-ramp;*

Step 2: *Check the status of the ramp-metering traffic signal and the VMS;*

Step 3: *Implement appropriate safe and fair actions so as to maximize the total traffic throughput on the main carriageway downstream the on-ramp according to traffic conditions in Step 1 and the status of the ramp-metering signal and VMS in Step 2;*

Step 4: *Using the results of actions undertaken in Step 3, update the learning process of the ramp-metering system and go to Step 1.*

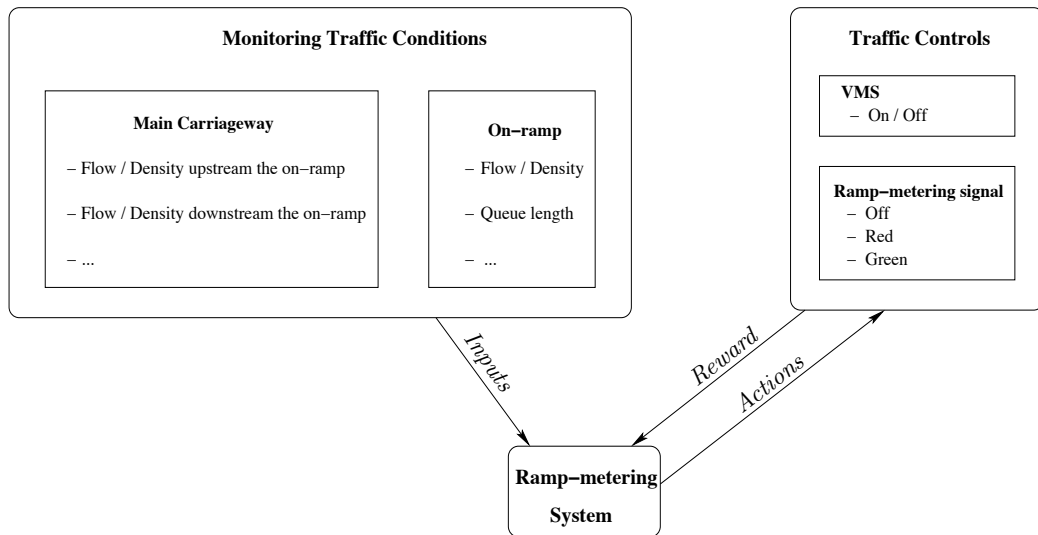


Figure 3. Overview of the operational structure of the proposed framework for local ramp-metering control.

In contrast with existing traffic control models based on reinforcement learning, e.g. [1], [24], the framework proposed in this study is designed for macroscopic traffic simulation, hence it enables to model traffic dynamics in crowded road networks. The most distinctive feature of the proposed ramp-metering scheme is its simplicity to implement and to operate. Furthermore, it does not require a supervision of the learning process

4. Case study and numerical experiments

In order to illustrate the proposed framework, we consider an isolated ramp-metering system for a freeway on-ramp, as depicted in Figure 2. Traffic dynamics along road sections is described using the LWR model (2.1)-(2.3) with the following parameters' values: $v_{max} = 130$ km/h, $\rho_{max} = 110$ vehicle per km per lane, whereas the maximum flow on the main carriageway is set to 2500.

Reinforcement learning approach is used to estimate the optimal ramp-metering rates that maximize the aggregated throughput on the main carriageway, downstream the on-ramp, see Figure 2. The boundary data from the LWR model serve as inputs for reinforcement learning and the output flow rates are used to update the boundary traffic data for the LWR model. Since ramp-metering control systems are generally helpful during busy traffic periods, we perform some numerical simulations of the proposed framework in such traffic conditions. The simulation setup is as depicted in Figure 2. We consider road sections of 400 meters on the main carriageway both upstream and downstream the on-ramp. Initially both road sections as well as the on-ramp are empty. The proposed approach is tested on the examples where boundary inflows for the main carriageway and the on-ramp are randomly produced. The simulation run time is 600 time steps where every time step corresponds to 0.1 minutes. In Figure 4 (left column) we plot the flow rates on the main carriageway in the vicinity of the ramp as well as the ramp-metering rate. Furthermore, in order to show more insights on traffic dynamics caused by the on-ramp on the main carriageway, we plot in Figure 4 (right column) the corresponding density profile on the main carriageway both upstream and downstream the on-ramp which is located at $x = 40$.

The sample numerical simulation results depicted in Figure 4 highlight some interesting features of the proposed framework. Indeed the model always targets the maximum aggregated throughput downstream the on-ramp while not disrupting the traffic on the main carriageway upstream the ramp. Thereby the ramp-metering scheme introduced in this work

is consistent with the main objective of local ramp-metering which consists of an efficient use of a freeway system during peak period so as the corresponding traffic flow is maintained within an immediate neighborhood of the maximal capacity of the road. Furthermore, although the inflows at the boundaries of the main carriageway and the ramp were randomly produced and fluctuated drastically, the model generates more smooth control actions – thus a smooth ramp-metering rates as shown in Figure 4 (left column). This interesting feature of the proposed scheme, which ensures more safety at on-ramps, is due to the ability of reinforcement learning approach to deal with a sequential decision making problem.

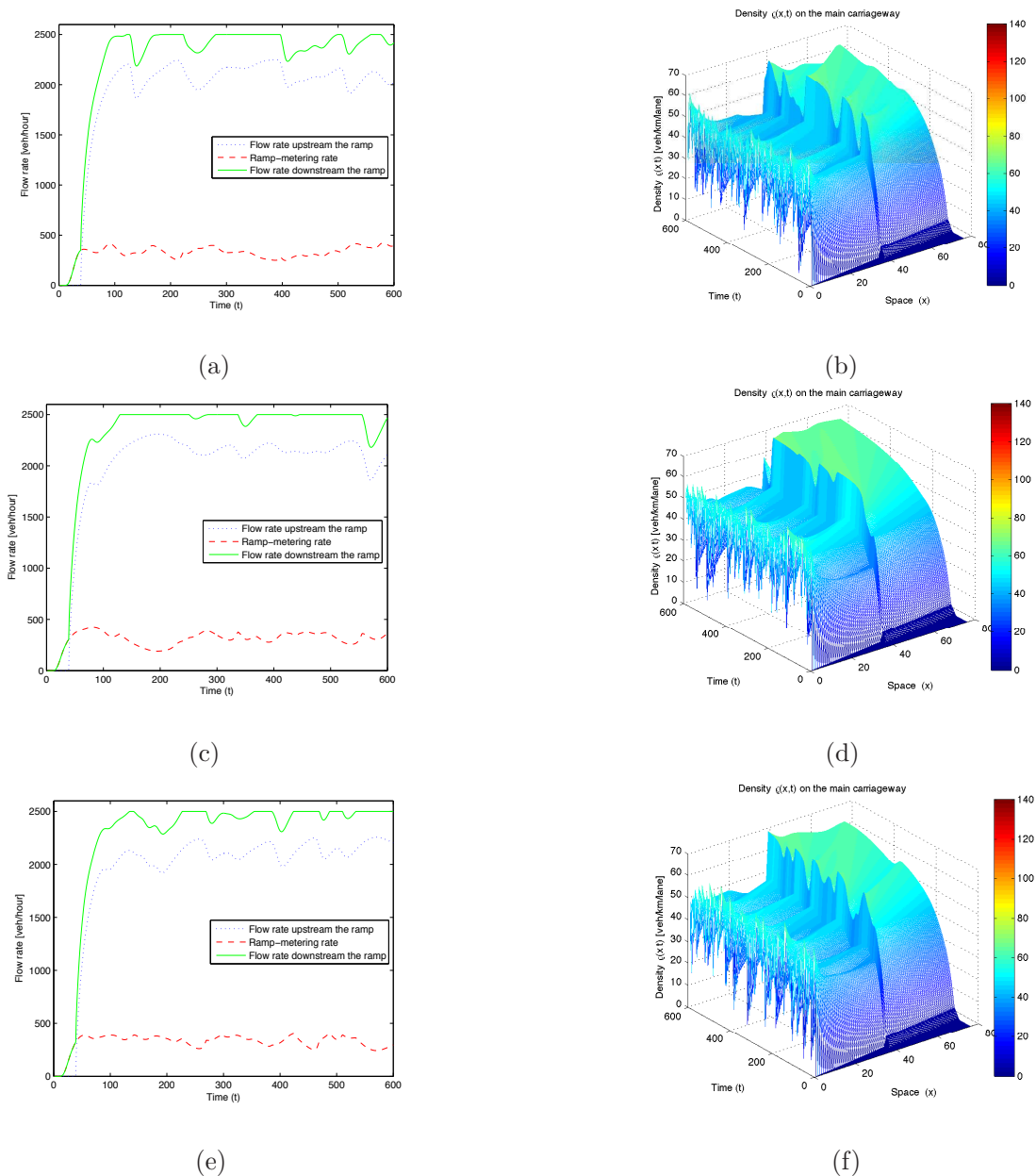


Figure 4. Sample simulations of traffic dynamics on the stretch of road depicted in Figure 2, using random boundary conditions: Flow rates in the vicinity of the ramp (left column) and the corresponding density profile on the main carriageway (right column).

5. Concluding remarks and outlook

This paper treats the problem of controlling freeway systems using ramp-metering systems in order to enhance their efficiency. More precisely, we introduce a local ramp-metering scheme which combines the LWR continuum model of traffic flow with reinforcement learning approach. The experiments show that the proposed ramp-metering scheme performs well in maximizing the aggregated flow on the main carriageway downstream the on-ramp, during busy traffic period. Furthermore, the obtained results comply with some additional features required for ramp-metering systems, such as equity and safety. The results presented in this study concern an isolated on-ramp of a freeway network, and therefore the natural extension of the study is to extend the approach so as to coordinate automatically and in an optimal way a network of ramp-metering signals. Thanks to their ability to cooperate toward a globally optimal policy, reinforcement learning models, in particular multi-agent reinforcement learning models, could be suitable for a such extension. Furthermore an extension of the framework to higher order continuum models e.g. [2] and multi-class continuum models e.g. [10] as well as an application to real-life and a comparison with ramp-metering control models in the literature are worthwhile in order to show more insights on the effectiveness of the proposed framework.

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