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Development and Evaluation of Collaborative Ramp Metering Control for Congested Urban Freeways

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Development and Evaluation of Collaborative Ramp Metering Control for Congested Urban Freeways

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Executive Summary

ADAS and autonomous vehicles allow new control paradigms in traffic management. As the time horizon for driverless cars technology shifted forward in the future, collaborative driving and communication open new possibilities in the next 5-10y to realize control policies aimed at increasing safety, reducing congestion and dissipate waves. Collaborative driving results are available for vehicle level controls and mostly focused on architecture and human-in-the loop approaches. We aim at a macroscopic and network-level approach to exploit the potential impact of collaborative driving.

Based on the models and controls developed in Task 1, the ramp metering problem in urban and highway setting will be addressed also using a hybrid approach to lane merging modeling and distributed modeling. The control algorithms designed in Task 1 will be tested numerically using the Flow (open-source simulation environment managed by UC Berkeley) or a more generic simulation tool namely, SUMO. A simulation model of an urban freeway with a connection to a major arterial will developed and calibrated to ensure the realism of the simulation-based analysis. In addition to the simulation model development, API capability of the simulation tool will be used to simulate CAVs that have different control and communication capabilities.

Two ramp metering scenarios were designed for urban and highway setting. The simulations will be based on the open-source micro-simulator SUMO. The control algorithms will be tested for performance measured in terms of congestion reduction and fuel economy. Parameter optimization of the controller were performed using the optimization tools of the Flow environment. The response of the Eulerian and Lagrangian based ramp metering control were tested under various disruption conditions. The effectiveness of CV based results show that a small percentage of CAVs on the highway congested area will be able to smooth the traffic flow efficiently.

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1. Introduction

1.1 Background and Motivation

Ramp metering, also known as ramp control or ramp signaling, is the practice of controlling the flow of traffic onto a highway using traffic signals. The goal of ramp metering is to reduce congestion and improve traffic flow on the highway. Ramp metering has its roots in the early days of highway design when engineers began to recognize the need to manage the flow of traffic onto busy highways. The first ramp metering systems were installed in the United States in the 1960s in Chicago Eisenhower Expressway, as well as other locations, for instances Los Angeles, and Detroit. Initially, police officers were used to manually meter the flow of vehicles onto the freeway at predetermined rates, which resulted in smoother merging and improved safety. Over time, manual metering was replaced with traffic signals and gates, and coordinated ramp metering was introduced. In the 1980s and 1990s, traffic-responsive ramp metering became more common, and in 2006, Caltrans implemented adaptive ramp metering in the Los Angeles area.

Ramp control systems regulate the flow of vehicles at ramps in order to achieve specific goals such as balancing capacity and demand or improving safety. Freeway ramps are the only legal points of entry and exit for vehicles on a freeway, so they are the only places where control can be exercised. When vehicles try to merge onto a busy freeway, they may have trouble finding a spot in the flow of traffic due to high volumes. This can lead to vehicles lining up on the entry ramp, forming a queue and waiting until they can enter the freeway. This congestion can cause delays, decreased comfort levels, and an increased risk of accidents.

Modern systems often use multiple traffic signals and sensors to monitor traffic flow and adjust the signal timing in real-time. Some systems also use various algorithms to optimize signal timing and reduce congestion. Ramp metering is now widely used in many countries around the world, and it is considered an effective tool for managing highway congestion to accommodate high volume demand. Ramp control has been shown to have many positive benefits, such as reduced delay and travel time, increased throughput and operating speeds, and reduced accidents. These benefits are commonly reported in the literature and are supported by case studies, which are summarized as follows:

- Mobility: Ramp control systems can influence freeway traffic characteristics such as speed, travel time, and delay. Highway arterial management systems typically aim to optimize throughput while maintaining non-congested conditions. By controlling the number of vehicles entering the freeway, ramp control can enhance freeway operation.

- Safety: Ramp metering can decrease the number of vehicle crashes on both merging area and on the freeway. By coordinating vehicles that enter the ramp from adjacent intersections or traffic origins, the incidence of rear-end collisions is reduced. With collaborative ramp metering control drivers in the outside lane are less likely to have to brake suddenly or change lanes. Overall, ramp control can reduce the likelihood of crashes caused by disturbing traffic.
- Emission Reduction: Improved system operation can directly and quantifiably reduce fuel consumption. Fewer stops and speed changes can lead to reduced fuel consumption and more uniform speeds. However, these improvements must be balanced against the potential for increased delays and travel times for diverted travelers.

Ramp metering is a common traffic management strategy used in many areas, but the specific details of how it is implemented can vary depending on local conditions and the policies of the agency responsible for managing the highways. In this research, we will develop a novel local ramp metering strategy based on social cyber-physical modeling using the Mean-Field-Game theory and test the model results considering normal conditions and bottlenecks down streams.

1.2 Research Objectives and Tasks

- Task 1. Definition of mean-field multi-scale models for collaborative driving and V2X communication and design of control algorithms for ACC and enhanced perception.

In a mean field game, the actions of individual players collectively affect the behavior of the group and vice versa. This type of game is used to model complex systems with many interacting components, such as markets or networks. In this way, mean field games capture the interactions between individuals and the collective behavior of the group. In the context of transportation networks, the mean-field game framework is used to understand the interactions between a large population of agents, and the congestion that results from these interactions on roads and at intersections. In this research, the ramp metering algorithm will be formulated as a constrained mean-field game considering the collaborative driving and V2X communication.

- Task 2. Study case for ramp-metering: congestion decrease and safety. Numerical tests in Flow using Sumo.

For this task, microscopic simulation framework SUMO-Flow will be utilized to analyze the effectiveness of proposed model under non-bottleneck conditions. Baseline algorithms will also be used to manifest the mobility and safety improvements through designed ramp metering algorithms. Both classical Asservissement Linéaire d'Entrée Autoroutière (ALINEA), a local feedback ramp-metering strategy as well as machine learning approach will be implemented.

- Task 3. Study case of disruption scenarios for ramp-metering: accident on the downstream of a work zone that requires a lane change.

For task 3, bottleneck scenarios with different downstream distances will be tested, which cause traffic congestion and delays for vehicles attempting to enter the highway. This is because the bottleneck restricts the flow of vehicles onto the highway, preventing them from maintaining a steady flow of traffic. It is important for traffic managers to monitor for downstream bottlenecks and implement strategies to mitigate their effects on traffic flow.

2. Literature Review

2.1 Case Scan of Ramp Metering

When implementing ramp metering, many factors must be made that affect its performance, including but not limited to geographic features of merging area, metering algorithms and parameters, managing queues on both ramp and freeway, mainline volume and speeds, ramp storage and acceleration distances. All these factors should be considered when design the simulation environment that can significantly impact the effectiveness of developing ramp metering strategy. To help make these decisions, agencies have developed guidelines for implementing ramp metering. As previously mentioned, not all freeway sections are suitable for implementing ramp metering as a traffic management strategy. As a result, vehicles may have to wait longer at the ramp before they are able to enter the highway, leading to increased congestion and potentially causing delays for other vehicles on the road. Therefore, it is necessary to determine the conditions under which ramp metering can effectively improve traffic conditions. Currently, ramp metering is widely used in several major US cities, including Miami, Chicago, Los Angeles, Minneapolis/St. Paul, New York, Phoenix, Seattle, Denver, Las Vegas, Kansas City, Northern Virginia, Philadelphia, Columbus, Salt Lake City, Milwaukee, and Atlanta. Many other metropolitan areas also have smaller ramp metering systems in place. In the following parts, we will scan the current practices from major state DOTs in the United States and reported ramp metering implementations from countries around the world.

- California DOT

According to 2017 Caltrans (California Department of Transportation) Ramp Metering Development Plan, there are total of 3014 exiting ramp metering signal controllers deployed statewide and additional 1838 ramp metering are planned, which accounts for the largest amounts of state-operated ramp metering facilities in the US. Most ramp meters in the California are local traffic responsive, which are typically operate based on local traffic conditions and may use fixed or adaptive metering rates. The metering rate is determined using vehicle detection systems that monitor traffic on the freeway. In order to improve mobility, safety, and reduce the energy and emissions impact of congestion on the freeway, The University of California PATH program modified ALINEA algorithm for use in ramp metering and traffic signal control on the Route 99 freeway corridor. The reported travel time reduction rates range from 9% to 37% from different freeway segments.

- Minnesota DOT

The first ramp metering installed by Minnesota Department of Transportation is located on I-35E at the entrance ramps from Maryland Ave and Wheelock Parkway in St. Paul in 1969. The Twin Cities Metro Area has 433 meters, which aren't running all day. Some operate only in the morning peak, some only during the afternoon peak, and others during both peaks. According to the data collected at Minnesota, ramp metering reduces 22% travel time and increase 9% throughput on freeway. The traffic speed is increased by 7%, and travel time reliability is increased by 91%. A 9 percent reduction in freeway volume. In terms of safety, crash rates were decreased by 26% after averaging for seasonal variations (Cambridge Systematics Inc, 2001; Hourdakis and Michalo-poulos, 2007).

- Florida DOT

Florida DOT currently manages 54 ramp signals on District-4 I-95 Managed Lane, 11 ramp signals on I-4 Managed Lane in District-5, 41 ramp signals on District-6. Haulewas et al. (2021) analyzed the data from a corridor with system-wide ramp metering along I-95 in Miami, Florida. The study area was a 10-mile section, which has a fully operational ramp metering system with 10 ramp metering signals (RMSs) in the northbound direction, and 12 ramp signals in the southbound direction. Two years of data from 2016 to 2018 were used in this analysis, including real-time traffic, crash, and ramp metering operations data. The results revealed that ramp metering could help reduce the crash risk on freeway segments within a range of 12%–14%.

- Arizona DOT

According to the ramp metering design manual used by the Arizona Department of Transportation (ADOT), the installation of a ramp meter is based on two warrants. The first warrant is Freeway right lane and entrance ramp flow rate. The second warrant is based on freeway speed (Simpson and Yasmin, 2013). Multi-objective, Integrated, Large-Scale, Optimized System (MILOS) algorithm was at the University of Arizona, taking traffic demand data from detectors on the freeway and entrance ramps to determine a metering rate In 2017, ADOT switches their ramp control strategy from fixed-time to responsive control and used loop detector data and INRIX data to understand the extent of data required for assessing its new ramp metering strategy (Ma, Karimpour and Wu , 2020).

- Washington DOT

The Washington State Department of Transportation conducted a study on I-405 to evaluate the effects of different ramp meter controller logics. The new software was installed in 9 ramp meter controllers for the study. The results showed that the new logic reduced travel time during the morning commute, but not during the afternoon. A study on I-90 showed that fuzzy logic-based ramp metering could reduce 8.2% mainline congestion (Chu et al., 2004). Another study (Taylor and Meldrum, 2000) on I-405 showed that fuzzy logic has 1.2% worse than bottleneck-based metering algorithms.

- International Cases

Study from England found that the travel time for mainline traffic was reduced 13% during the morning peak hour when ramp metering was implemented (Hayden et al., 2009). The traffic throughput is increased ranging from 1% to 30% depending on different sites. Study from Netherland (Middelham and Taale, 2006) could increase average speed and decrease the travel time and improve overall capacity by 5% with fuzzy logic control algorithms. One research from Australian Melbourne (Papamichail et al., 2010) reports that ramp metering increases 4.7% traffic volume in the morning peak hour and 8.4% for afternoon peak hour. The travel speed was increased 35% and 58.6% for morning and evening peak hour respectively. Another study from Brisbane Australia (Faulkner, 2014) obtained 7% speed improvement and 4% traffic flow improvement with local ramp metering algorithm.

2.2 Typical Ramp Metering Algorithms

Local ramp metering and System-Wide Coordinated Ramp metering are two common classifications. Local ramp metering is typically done using vehicle detection sensors located on the proximity of the single ramp. One advantage of local ramp metering is that they can be turned on and off as needed based on traffic conditions. The disadvantage of local ramp metering is that local traffic-responsive metering does not consider what is happening on the rest of the system. Some local traffic-responsive systems also can manage demand rates in the event of incidents on the freeway, such as accidents or road closures. System-wide traffic-responsive ramp metering uses vehicle detection sensors along the entire length of a freeway to coordinate the flow of vehicles entering the freeway from multiple entrance ramps. This method allows the metering rate at any ramp to be influenced by conditions at other ramps, resulting in a more comprehensive traffic management strategy. In order to implement this method, a centralized computer-controlled system with the necessary communication infrastructure must be in place. When selecting a ramp meter control strategy, it is important to consider various factors such as the extent and location of congestion, as well as issues of equity. If congestion is limited to a few isolated ramps, a local control strategy may be more suitable. However, if congestion occurs at multiple locations that are close together and largely contiguous, an area- or system-wide control strategy may be more appropriate. Equity is also a factor to consider, as it may be perceived that certain areas benefit at the expense of others. If this is a concern, an area- or system-wide control strategy may be more suitable. In this study, we will mainly focus on local ramp metering strategy and leave coordinated system-wide ramp metering strategy for future research. Kontorinaki, Karafyllis, Papageorgiou (2019) developed a unifying scheme that can be applied to both local and coordinated levels, based on a recently developed nonlinear adaptive control scheme, consisting of a nominal feedback law in conjunction with a nonlinear observer.

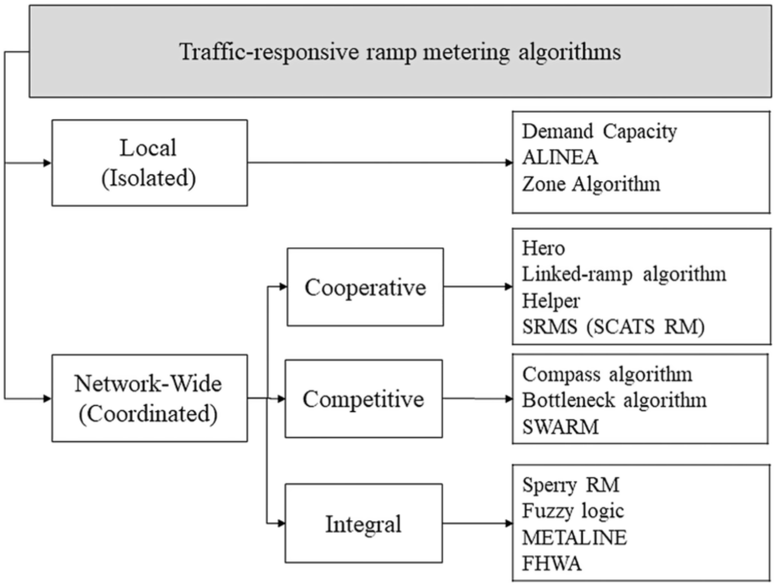


Figure 1. Ramp Metering Categories

(Grzybowska, 2022)

The ALINEA ramp metering strategy uses local feedback to maximize freeway throughput by maintaining desired occupancy (Papageorgiou et al., 1991). It only requires one freeway detector per lane downstream of an entrance ramp and provides closed-loop, traffic-responsive control. ALINEA uses a single freeway detector per lane, installed downstream at 40 or 400 meters. The detector measures the current occupancy rate and sends the information to the controller at regular intervals. The controller then calculates the difference between the desired occupancy threshold and the measured occupancy and uses this information to determine the metering rate for the next interval. The algorithm also considers the previous metering rate to avoid sudden changes and ensure smooth operation. The goal of ALINEA is to set the metering rate at a level that does not exceed the freeway's capacity. Several modifications have been made, including PI-ALINEA (Wang et al, 2014), UP-ALINEA (upstream-occupancy-based version), UF-ALINEA (upstream-flow-based strategy), AD-ALINEA (Adaptive – with estimation algorithm to o_{cr}), XALINEA/Q combination of any of the preceding strategies with efficient ramp queue control) (Smaragdis et al., 2004).

The ALINEA algorithm uses the following equation for deriving ramp metering rates for each period k = 1, 2 … (e.g., every minute).

$$r(k) = r(k-1) + K_R[\hat{o} - o_{out}(k)] \qquad (1)$$

Where:

- $\hat{o}$ is the desired occupancy rate downstream of the ramp,
- $o_{out}(k)$ is the measured occupancy rate downstream of the ramp,
- $r(k{-}1)$ is the measured onramp volume for time interval k-1, and
- K_R is a regulator parameter which is greater than zero.

The Bottleneck algorithm, which was developed by the Washington State Department of Transportation in response to growing congestion problems in the Seattle area, provides both local and system-level control on a selected freeway section by using a look-up table to determine the metering rate based on upstream demand and downstream capacity (Jacobson et al., 1989). It operates at both the local and system-wide levels. At the local level, the algorithm compares the free demand at the upstream of the ramp and the capacity at the downstream of the ramp and calculates the optimum metering rates that ensure that demand does not exceed capacity. At the coordinated level, the control algorithm is activated when the occupancy at a potential bottleneck area exceeds a threshold and there is a queue of vehicles upstream of the bottleneck. The coordinated control then determines the metering rates for all meters in the area or zone to reduce the volume of vehicles entering from the ramps to the bottleneck area, so that it is equal to the volume in the upstream queue on the mainline. Once the metering rates have been calculated for each ramp using both local and coordinated control, the more restrictive rate is applied. The activation of Bottleneck algorithm is based on two conditions: the capacity condition measured from downstream detectors' occupancy and vehicle storage condition that is used to describe the total income volume from onramp and upstream freeway is greater than the exiting volume of off-ramp and freeway outlet. The metering rate is calculated as the following:

$$BMR_{ji(t+1)} = q_{ON_{jt}} - MAX_{i=1}^{n}\left(\frac{U_{i(t+1)}{*}WF_j}{\sum_j^n (WF_j)_i}\right) \qquad (2)$$

Where $BMR_{ji(t+1)}$ denotes the bottleneck metering rate of ramp j. $q_{ON_{jt}}$ is the entrance volume on ramp j during the past minute. $U_{i(t+1)}$ is upstream ramp volume reduction for segment i to be applied on the next metering interval $(t + 1)$. WF_j is the weighting factor for ramp j. $MAX_{i=1}^{n}$ is the operator of selecting the maximum volume reduction if a ramp is inside of multiple areas of influence. $U_{i(t+1)}$ is calculated using total entering volume minus total exiting volume. (Karim, 2015)

The Corridor Adaptive Ramp Metering Algorithm (CARMA) is a system-wide adaptive strategy that uses mainline speeds and ramp conditions to set the metering rate. CARMA allows ramp meters to be activated based on traffic demand (Sims, 2011). The algorithm system, CARMA, computes metering rates at each mainline vehicle detector station based on smoothed mainline speeds. The CARMA algorithm provides interconnection among the ramps based on downstream conditions, maximum and minimum rates, ramp queues, and hours of operations.

The Fuzzy Logic algorithm is used in Seattle and Miami metropolitan area, which was developed by the University of Washington (Taylor, C., D. Meldrum, 1998; Tian et al. 2002). Inputs of this detector include upstream occupancy, occupancy at merge, downstream occupancy, downstream speed, speed at merge, queue occupancy, and advance queue occupancy (Vukanovic and Ernhofer, 2006). Ghods et al. (2009) utilized variable speed limits (VSLs) in addition to the fuzzy controller, for congestion management to regulate highway traffic flow. On the same network with the same base circumstances, the outcomes of the fuzzy controller with and without VSLs were compared with those of the normal ALINEA implementation and no control. The findings demonstrated that the genetic fuzzy logic-based ramp metering produces traffic conditions with less congestion. In comparison to ALINEA, the comparisons revealed an increase in travel time saving (5% Without VSLs and 15.5% With VSLs).

Zone algorithms divide the freeway into multiple zones of varying lengths, from 3 to 6 miles, with multiple metered and non-metered ramps. The algorithm maintains the density on the mainline below a certain threshold by controlling the inflow and outflow in the zone. The collective metering rate is calculated from the inflow and outflow values and then distributed among all ramp meters using pre-defined ramp factors. The goal of this algorithm is to control the total volume of a segment of the freeway, known as a "zone". The increase in mainline density is balanced by lowering the metering rates in the zone. The Zone algorithm calculates metering rates for each zone by the following equation (Chu et al. 2002).

$$M + F = X + B + S - (A + U) \quad (3)$$

Where, M denotes total metered onramp volumes; F denotes total metered freeway-to-freeway volumes; X denotes total measured off-ramp volumes; B denotes downstream bottleneck capacity; S denotes space available within the zone which can be calculated using measured freeway occupancy; A denotes Total upstream freeway volume, and U denotes total measured non- metered ramps volume.

Stratified Zone Metering (SZM) -The Minnesota Algorithm uses density measurements to ensure more vehicles exit than enter the freeway to relieve congestion. The ZONE metering strategy has been successful in reducing congestion on the Twin Cities' freeways for many years. However, excessive ramp delays due to high demand on specific ramps led to a study that shut down ramp meters for eight weeks. The study (Michalopoulos, Hourdos and Xin, 2005) confirmed the overall benefits of ramp metering, but also showed that the ZONE metering strategy's focus on maximizing freeway throughput led to unchecked ramp queues and unacceptable ramp delays and spillbacks. In response, MnDOT modified the control objective to implement a queue control policy and developed the Stratified Zone Metering (SZM) algorithm. The new strategy still aims to maximize freeway throughput, but with an added constraint to limit the waiting time on ramps to a predetermined maximum. The implementation of SZM in the Twin Cities began in March 2002, and its full deployment was recently completed.

Heuristic ramp metering coordination (HERO) algorithm can be used for both local and coordinated control schemes. The HERO algorithm was created by Papamichail et al. (2010) and was first implemented on the Monash Freeway in Australia. It is an improved version of the ALINEA cooperative ramp control algorithm, which controls individual traffic lights at a junction but also connects them through a central control system. When there is a congested area, or bottleneck, near a particular traffic light (referred to as the "master" light), the central control system will enlist other nearby traffic lights (referred to as "slave" lights) to help increase the capacity of the master light and alleviate the congestion. HERO uses measurements taken at the traffic light junction to determine when to activate this process. Belisle et al. (2019) evaluated HERO Ramp-Metering Algorithm with San Diego’s Integrated Corridor Management System Model, finding that HERO was found to outperform all the other algorithms: gains of 1.5% over ALINEA and 4% over do-nothing on the mainline average travel time.

Helper Algorithm (also known as Denver Ramp Metering Control Software) is a real-time local traffic responsive ramp-metering application on five onramps on northbound I-25 freeway in Denver, Colorado, which was developed by the Colorado Department of Highways in 1981 (Lipp et al. 1991). The implementation evaluation reveals that freeway speeds increased 58%, and travel time was decreased by 37%. The Helper algorithm is a traffic control system that combines a local traffic-responsive algorithm with the ability for central control to override it. Each traffic light adjusts its metering rate based on local traffic conditions and uses detectors to gather information about traffic on the main road. If the queue of cars waiting to enter the main road extends back to the cross street, the metering rate is increased. The system coordination plan is activated if both the ramp and the main road are congested, which involves reducing the green time at the next upstream traffic light and potentially the next two upstream traffic lights if congestion persists.

2.3 Theoretical Algorithms

The above ramp metering methods were developed and implemented in the field by several states' Department of Transportation. There are many research groups that developed ramp metering strategies under simulated environment. Zhang and Ritchie (1997) developed neural network model for local ramp metering. The control metering rate is minimizing the differences between target density and current density as well as the difference between target flow and measured flow. Klomp et al. (2022) proposed a gap detection-based ramp metering approach and compare the results in simulation with macroscopic ramp metering and no-control systems.

Fares et al. (2014, 2015) designed Reinforcement learning based density control agent (RLCA), which is a density control agent that uses reinforcement learning based on a Markovion model and a Q-learning algorithm to handle the stochastic nature of traffic conditions. The author evaluated the proposed definition of (state, action) pairs and the reward function using two case studies with different network structures and demand levels: a dense demand network and a light demand network. After the RLCA, Multi-agent Reinforcement Learning (MARL) was developed to different network architectures: fully independent, fully distributed, and centralized. VISSIM was used to test the performance of our framework in heavy traffic conditions. The results showed that RL method led to a significant reduction in total travel time and an increase in average speed compared to the base case, while maintaining optimal traffic flow.

Zhao et al. (2011) designed a dual heuristic programming (DHP) method to coordinate ramp metering in freeway systems, aiming to optimize the management of both recurrent and nonrecurrent congestions with queuing considerations. The simulation results show that the DHP method, which uses approximate traffic models for offline development, outperforms the classical ramp metering algorithm ALINEA in maintaining good control performance. In this study (Davarynejad et al., 2011), the performance of a standard Q-learning algorithm and a newly proposed multi-criterion reinforcement learning algorithm is evaluated in the context of a local ramp-metering control problem that takes into account the presence of queuing. The results of the experimental analysis suggest that the proposed multi-criterion control approach can effectively reduce the size of the state space, accelerate the learning speed of the controller, and improve the quality of the solution.

Rezaee et al. (2012) developed kNN-TD RL controller using the loop detectors for the training and deployment phase of the RL agent using real-life data from Highway 401 in Toronto. Ramp metering using Model predictive control (MPC) was studied by Muralidharan and Horowitz (2015) and Roncoli et al. (2015) based on other variants of the cell transmission model, taking variable speed limit control, downstream capacity drops into account. Hou et al. (2021) developed Reinforcement Learning-based ramp metering algorithm in connected environment. Georgantas et al. (2022) developed Explicit Model Predictive Control (EMPC) ramp metering strategy combing Variational Autoencoders (VAEs) to minimize the mismatch between actual control law and approximated control law, because, traditionally, EMPC performs well under abundant high-quality training data, while its approximation accuracy deteriorates with limited data.

Belletti et al. (2018) investigated how neural network-based reinforcement learning (RL) can be used to control discretized PDEs whose parameters are unknown, random, and time-varying. To address the curse of dimensionality often present in multi-agent control schemes, they proposed an algorithm called mutual weight regularization (MWR), which allows agents to share experience while still allowing them to specialize their action policies according to the local parameters of the part of the system they are located in. Using a neural RL PDE controller on a traffic flow simulation based on a Godunov discretization of the San Francisco Bay Bridge to demonstrate the benefits of proposed model.

Han et al. (2022) developed a physics-informed RL strategy using combination of historic data and synthetic data from a traffic flow model. Their approach improves systems total travel time spent savings and outperforms classical feedback ramp metering algorithms under simulation environments.

3. Definition of Mean-Field Multi-Scale Models

By connecting microscopic measurements from detectors to macroscopic traffic flow parameter, the mean-field game (MFG) provides a framework for deriving a corresponding macroscopic model, assuming that each driver's behavior is influenced by the traffic density through their utility function, and the evolution of the density must be consistent with each driver maximizing their own utility. As a result, the evolution of traffic density and velocity is described by a system of partial differential equations (PDEs) consisting of a Hamilton-Jacobi-Bellman equation describing the average driver's behavior and a conservation law. The relationship between velocity and density is dynamic, as in second-order models, and can be adjusted to fit empirical observations, such as the fundamental diagram, by selecting the mean driver's utility function appropriately (Chevalier et al., 2015). This approach allows us to model drivers in a game theoretical framework rather than as simple kinematic particles, which is a suitable framework to develop social compliant driving strategy to enhance safety and efficiency in mixed collaborative and automated environment.

Due to limited project time, in this study, a ramp metering strategy was developed based on combination of Lagrangian control and traditional ramp metering control algorithms. A more general frame for real-time merging traffic control described by Spiliopoulou et al. (2010) is implemented to mitigate the interruption of onramp vehicles to the freeway. In addition to the fixed location Eulerian control device, the Lagrangian flow smooth control with autonomous driving vehicles were also added, which is described in Vinitsky et al. (2018) using deep reinforcement learning.

3.1 Eulerian Feedback Control Algorithm

The control algorithm described here is designed to manage the flow of traffic through a merge area, with the goal of maximizing the exit flow from the merge area. The algorithm is divided into three parts: feedback control for exit flow regulation, distribution of entering flows, and translation of control decisions.

The first part of the algorithm, feedback control for exit flow regulation, is responsible for maintaining a target exit flow by adjusting the control devices (such as traffic signals or lane markings) in real-time based on measurements or estimates of the current flow. The second part of the algorithm, distribution of entering flows, is responsible for ensuring that the entering flows into the merge area are distributed evenly and efficiently, in order to maximize the overall exit flow. The third part of the algorithm, translation of control decisions, is responsible for translating the control decisions made by the first two parts of the algorithm into actual actions that can be taken by the control devices.

Overall, the control algorithm described here is designed to optimize traffic flow through a merge area, by maintaining a target exit flow, distributing entering flows evenly and efficiently, and translating control decisions into actions that can be taken by the control devices.

3.2 Lagrangian Control through Deep-RL

Lagrangian control algorithm described here is designed specifically for autonomous vehicles (AVs) and is intended to optimize traffic flow through a bottleneck or merge area by using reinforcement learning to train the AVs to act like a ramp meter. The AVs are able to control the flow speed and spacing of vehicles in their platoon and can coordinate with other AVs in adjacent platoons to facilitate easier merging. This control strategy is referred to as Lagrangian control, in reference to the trajectory-based actuation of the AVs, as opposed to Eulerian control which is based on the volume of the control volume. The use of reinforcement learning allows the AVs to learn how to effectively regulate the inflow of traffic in response to the formation or warning signs of congestion, with the goal of maximizing the outflow of the bottleneck. The algorithm can handle the complexity of lateral and longitudinal dynamics in multi-lane settings and can effectively control the flow of traffic even in the presence of stochasticity in platoon lengths and AV distributions.

3.2.1 Reinforcement Learning

This section appears discussed the use of reinforcement learning for optimizing the behavior of an agent in a given environment. Reinforcement learning is a type of machine learning that focuses on maximizing the cumulative discounted reward of a finite-horizon Markov decision process (MDP). An MDP is a mathematical framework used to model sequential decision-making problems, in which an agent takes actions in an environment in order to maximize its reward. In the context of reinforcement learning, the goal is to find a policy, which is a mapping from states to actions, that maximizes the cumulative discounted reward of the MDP. The policy is often represented using a neural network, with the network weights (also known as parameters) denoted by θ. The policy may be implemented using different types of neural networks, such as a Gated Recurrent Unit Neural Net (GRU), which is a neural network with a hidden state that allows the policy to have some memory. In the case of partially observable tasks, which conform to the structure of a partially observable Markov decision process (POMDP), the MDP is supplemented with a set of observations of the hidden states and an observation probability distribution. This can be useful in cases where the agent can only fully observe the hidden states (such as the positions and velocities of automated vehicles) on occasion and must store them in memory in order to make decisions.

3.2.2 Policy Gradient Methods

The use of policy gradient methods and Trust Region Policy Optimization (TRPO) to optimize the parameters of a neural network used as a policy in reinforcement learning. Policy gradient methods estimate the gradient of the reward with respect to the parameters of the policy, based on a set of state-action-reward pairs generated from experiments. TRPO is a specific policy gradient method that constrains the KL divergence between the original policy and the updated policy to be within a fixed bound, in order to prevent the noisy gradient update from shifting the policy in a bad direction. This helps to ensure that the policy updates are reliable and do not significantly alter the behavior of the system.

3.2.3 Action Space

The controller maps observations of the AVs and the surrounding environment to a mean and diagonal covariance matrix of a Gaussian distribution, and the actions taken by the AVs are sampled from this distribution. The control action is designed to be invariant to the number of AVs in the system and can be used to adjust the maximum speed of the AVs in different segments of the roadway. The AVs' dynamics are modeled using the Intelligent Driver Model. The velocity of autonomous vehicle is defined as:

$$v_j^{AV}(t+\Delta t) = \min(v_{AV}(t) + \alpha_{IDM}\Delta t, v_j^{max}(t))$$

$v_j^{max}(t)$ is the maximum speed by Reinforcement Learning agent. The $v_j^{max}(t+1) = v_j^{max}(t) + \alpha_{agent}$, where $\alpha_{agent} \in [-1.5, 1.0]$, which is the agent choose to decelerate or accelerate when autonomous vehicles enter the merge areas.

3.2.4 Implementation

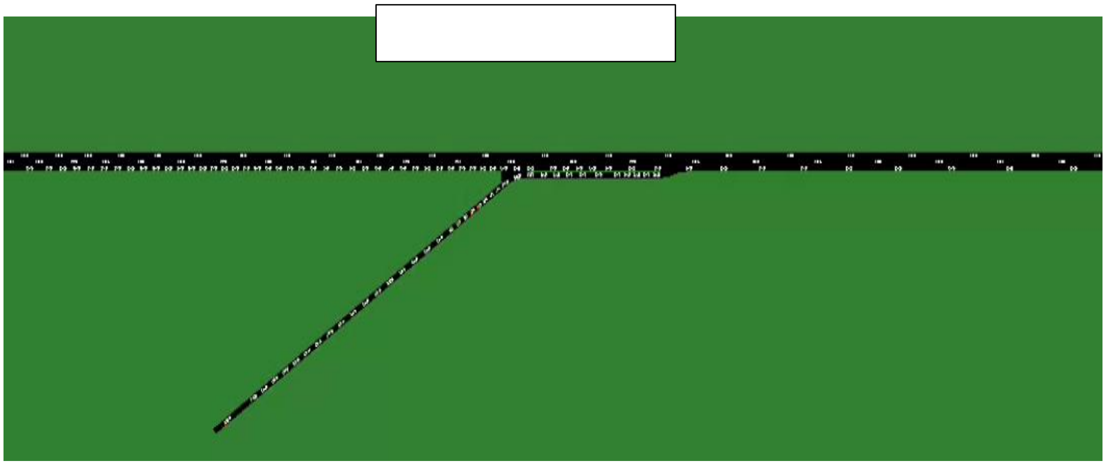
The Lagrangian algorithms were combined and implemented together for training a control policy for autonomous vehicles using reinforcement learning. The policy is parametrized as a neural network that maps observations of the AVs and their environment to a mean and diagonal covariance matrix of a Gaussian distribution, and actions are sampled from this distribution. The training process involves running simulations of the AVs in a traffic microsimulator called SUMO, and using the resulting states, actions, and rewards to train the policy using a reinforcement learning algorithm. The process is facilitated by a library called Flow, which provides an interface between SUMO and reinforcement learning libraries such as rllab and RLlib.

In the following sections, we will present our experiment results for two scenarios, including a typical freeway ramp metering section and ramp metering area with downstream bottleneck. Our goal is to decongest the congestion caused by onramp traffic volume and potential disturbances from downstream bottlenecks.

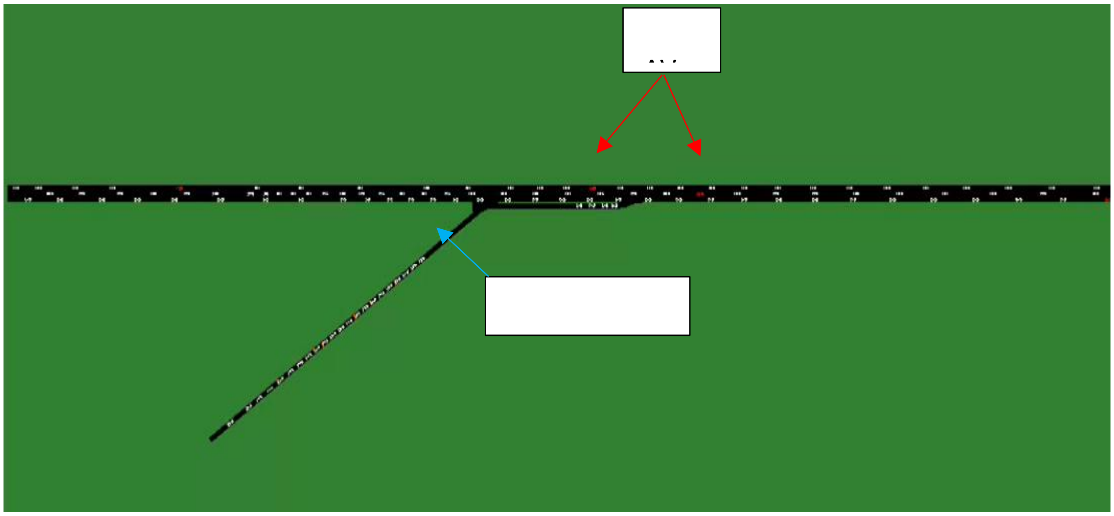
4. Study case for ramp-metering: congestion decrease and Sumo-Flow Simulation

4.1 Simulation Settings

With the default car following model parameters in SUMO, the observed mainstream freeway capacity is 2000 veh/h/ln for each lane, and the onramp capacity is 1000 veh/h/ln. This benchmark network structure can be found in (Ghods et al., 2009; Hegyi et al., 2005; Fares and Gomaa, 2014). The speed limit on the freeway was set as 65 mph, whereas the speed limit on the ramp was set as 40 mph. The lane order is numbered 0 ~ 2 from the innermost lane to the outermost lane on the freeway. Figure 2 shows the snapshot from both controlled and uncontrolled merging areas. In the controlled merging area, the Autonomous Vehicle with RL-controller is colored in red, while other human-driven vehicles are colored in white.



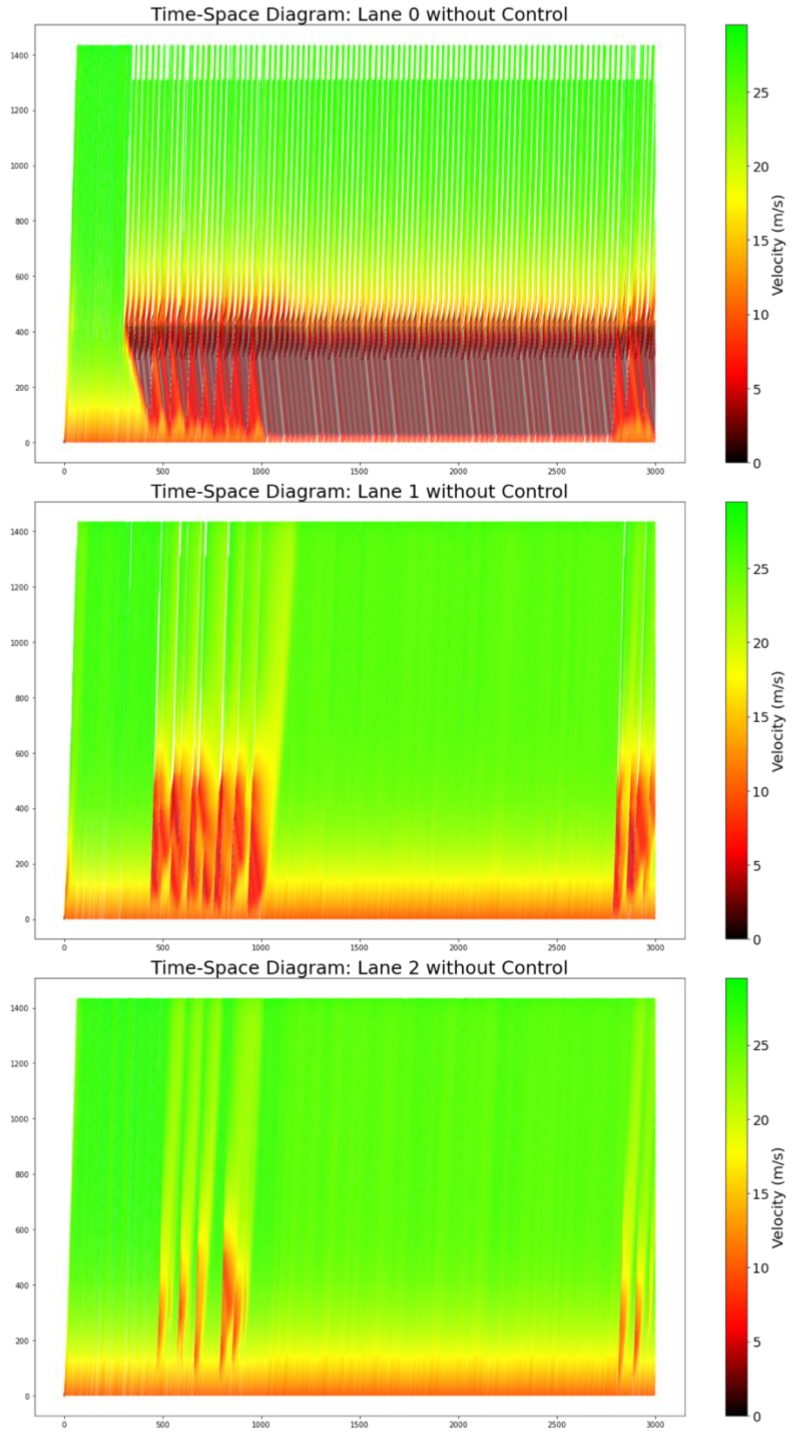
A. No Control Baseline



B. Controlled Onramp and Merging Vehicle with Proposed Methods

Figure 2. SUMO-Flow Simulation Network

4.2 Traffic Dynamic Analysis


Time-Space Diagram: Lane 0 without Control

Time-Space Diagram: Lane 1 without Control

Time-Space Diagram: Lane 2 without Control

Figure 3. Baseline Time Space Diagram for Each Lane on Freeway

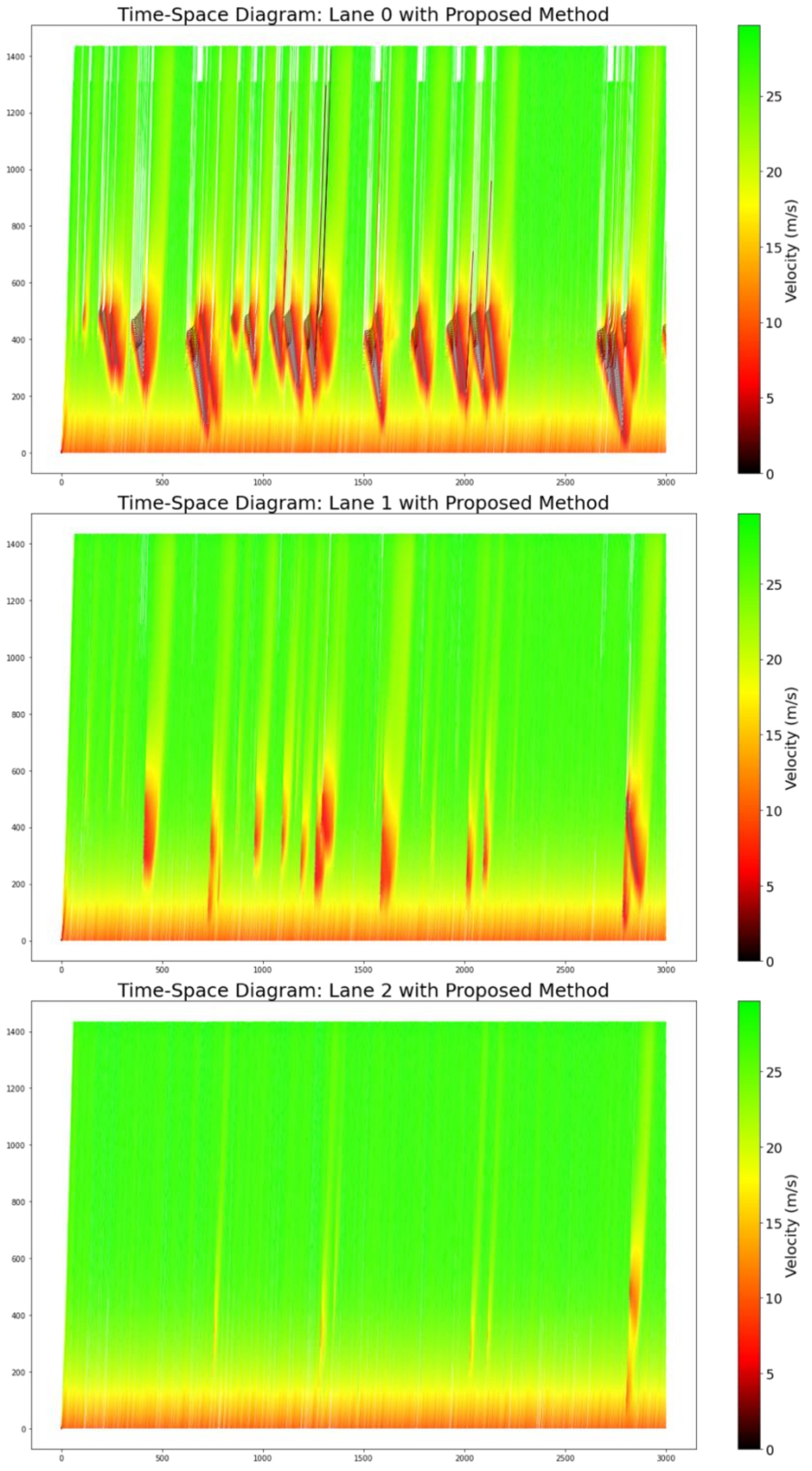


Figure 4. Controlled Time Space Diagram for Each Lane on Freeway

From the above two figures, we can see that the uncontrolled traffic flow will eventually end up with traffic congestion caused by onramp inflow traffic. The congestion originating from the innermost lane will impact its adjacent lane as well. After implementing the proposed method, the congestion induced by inflow traffic from the onramp is significantly mitigated in terms of temporal and spatial scope. The time-space diagram is also consistent with the snapshot shown in the previous figures—baseline conditions accumulated noticeable congestion on both the freeway's innermost lane and the onramp. On the contrary, controlled onramp flow only causes limited interruption to the freeway traffic. The metering algorithm has significantly reduced the severity of traffic split back.

Subsection 4.3

5. Study case of disruption scenarios for ramp-metering

5.1 Simulation Settings

This section adds the bottleneck to the previous network downstream to simulate a traffic accident or work-zone temporal traffic control, a typical nonrecurrent event for highway operation. Due to the downstream capacity drop, we set the inflow rate as 1100 veh/h/ln and the onramp inflow as 900 veh/h/ln, slightly below the total capacity of the entire highway segment. This inflow setting makes the traffic flow generate more dynamics while simultaneously being sensitive to breakdown due to outside disturbance and sudden capacity drop. As shown in the snapshots of both controlled and uncontrolled highway segments, vehicles jammed together at the weaving area, waiting to merge into the mainline traffic. Those onramp inflows force the mainline traffic to slow down and cause congestion. With ramp metering, the onramp vehicles were managed with a traffic signal to be released periodically according to downstream density. The second source of congestion is the bottleneck on the highway segment, where the 3-lane freeway was changed to a 2-lane freeway. The traffic disruption could result in traffic breakdown and brings about mile-long traffic jams. In addition, this disruption of downstream bottleneck could worsen the onramp weaving traffic to make the congestion much more severe to dissolve.

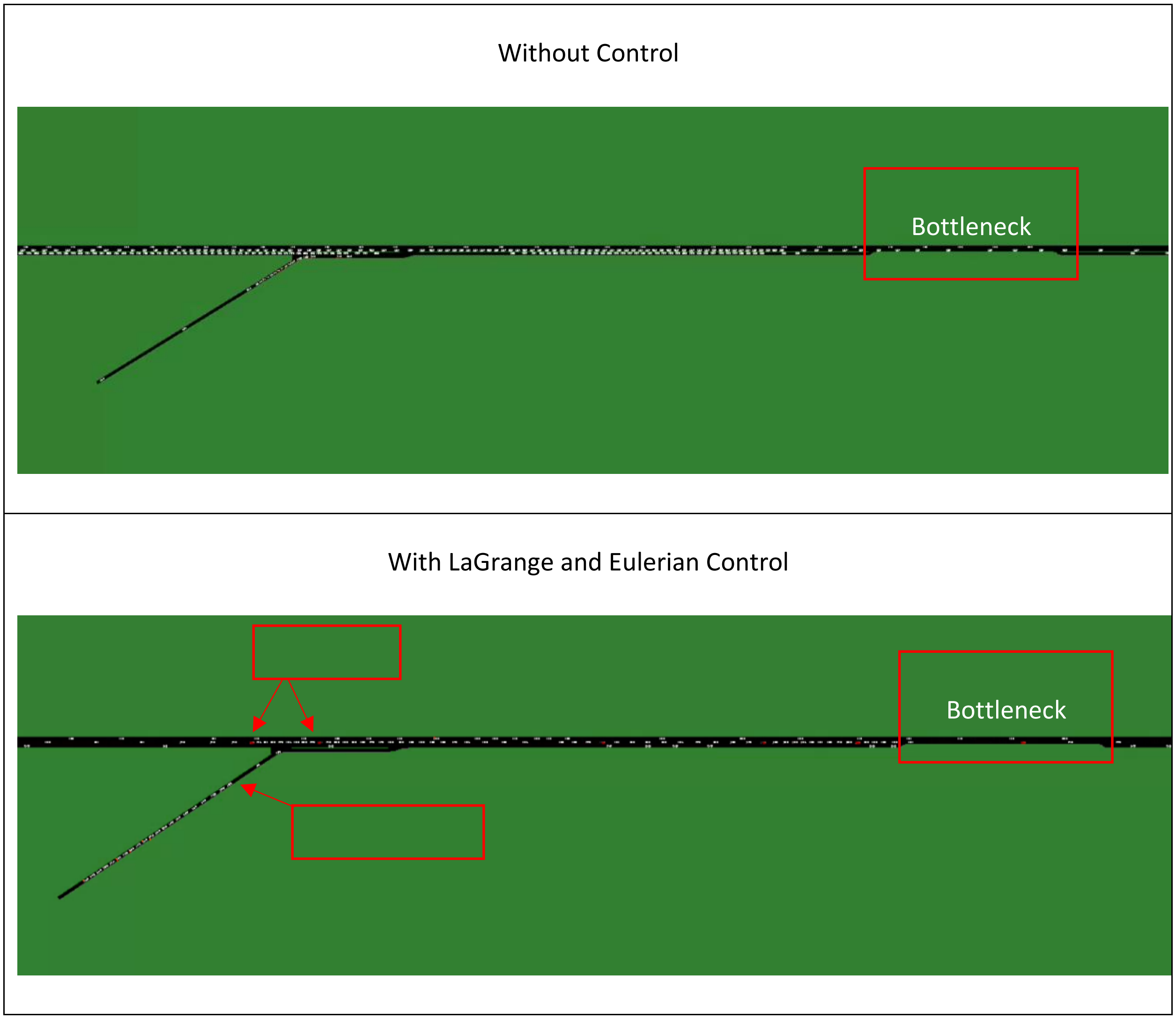


Figure 5. Case Study with Downstream Bottleneck

5.2 Traffic Dynamic Analysis

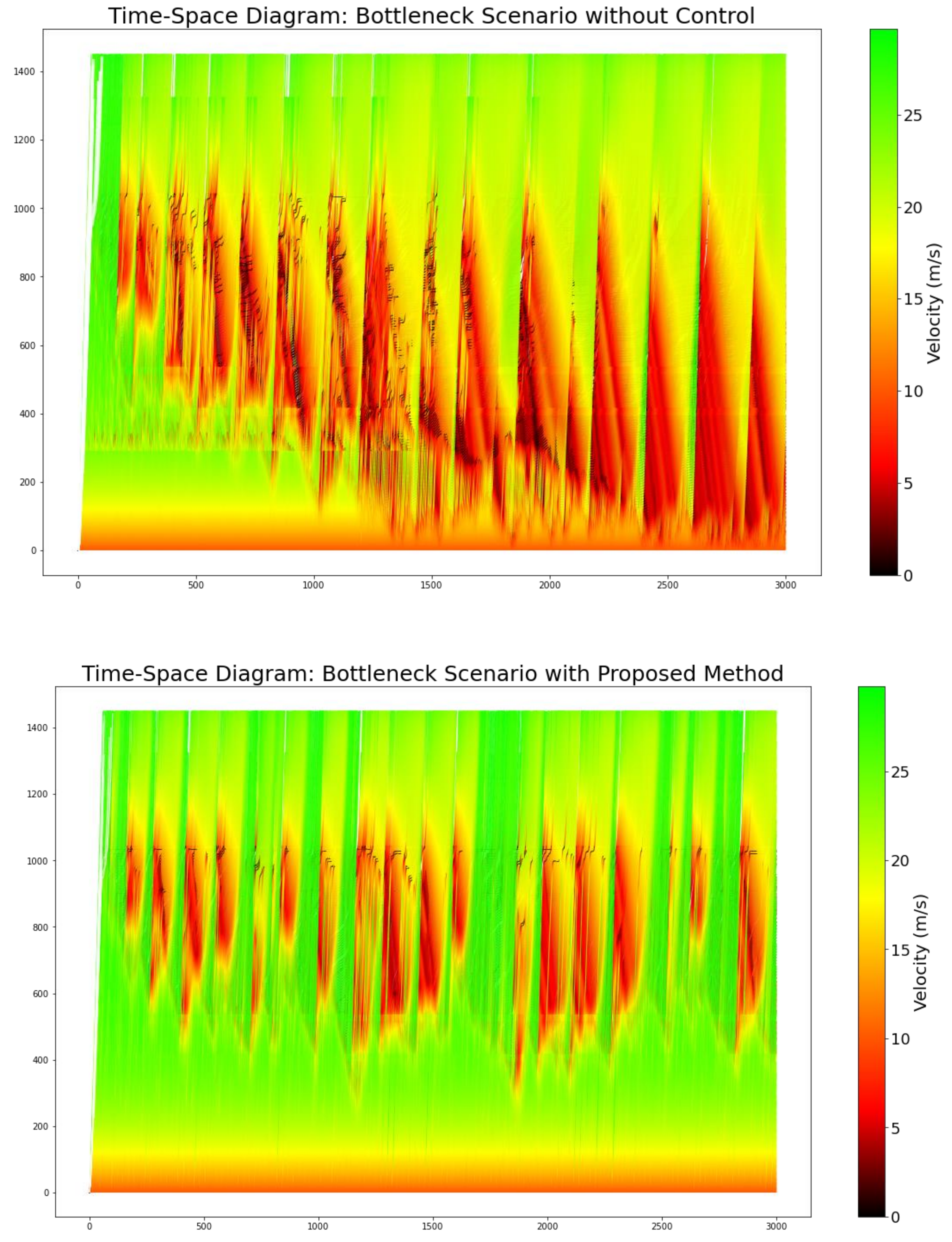


Figure 6. Time-Space Diagrams Under Bottleneck Scenario

From the time-space diagram in Figure 6, we can see that the traffic congestion in the uncontrolled highway segment continuously deteriorates in terms of scope and severity. The downstream bottleneck, coupled with merging disruption, eventually leads to the breakdown of the entire highway segment. In contrast, after implementing Lagrangian and Eulerian control algorithms, the congestion on the freeway section was restrained within a limited time and space scope. Furthermore, the Lagrangian ramp signal reduces the disruption of merging vehicles, and the Eulerian mobile AVs could improve the flow rate at the downstream bottleneck.

In Figure 7, the average speed of all vehicles on both the ramp and freeway was presented to demonstrate the effectiveness of the proposed methods. A the beginning of the simulation, the uncontrolled traffic could have a similar average speed with the metered strategy during the congestion formation period. However, as more and more vehicles travel into the area, the uncontrolled baseline can not release them, generating a large-scale traffic jam with an average speed of around 5 m/s. After implementing the ramp metering strategy, the interruption of onramp traffic has been minimized with the ramp signal. The downstream bottleneck congestion is mitigated with AVs that are trained to pass through the network bottleneck collaboratively.

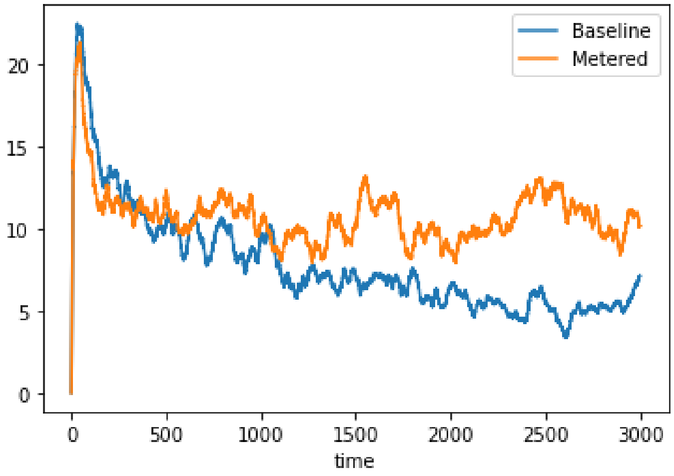


Figure 7. Average Speed Comparison Between Non-Metered Condition and Metered Condition

In Figure 8, the number of queuing vehicles was plotted to reveal the severity of congestion. With the proposed metering strategy, the queuing cars under the metering strategy are maintained below 20 cars, which means that the overall traffic can smoothly move to pass through this highway segment. However, if we remove the metering signal and AVs in the experiment, the system becomes very fragile. The number of queuing vehicles fluctuate between 0 ~ and 100. This plot shows that our proposed method is beneficial to improve travel time reliability and reduce travel time for road users not only for onramp traffic but also for freeway traffic.

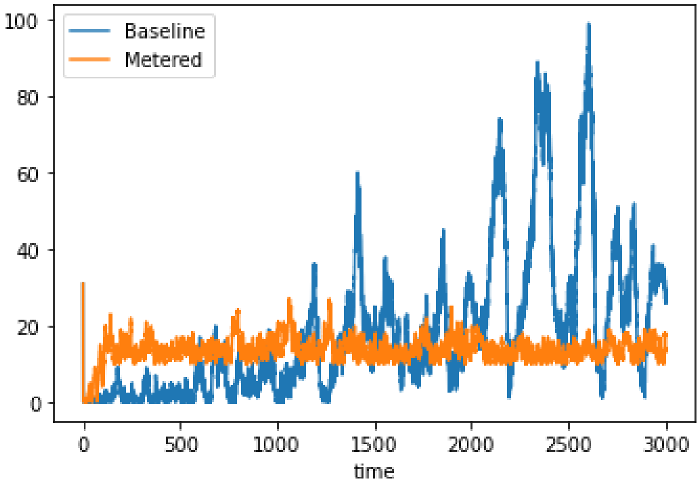


Figure 8. No. Of Queuing Vehicles for Non-Metered and Metered Conditions

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