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**MARYLAND DEPARTMENT OF TRANSPORTATION
STATE HIGHWAY ADMINISTRATION**

RESEARCH REPORT

**DESIGN AND DEMONSTRATION OF AN ARTERIAL-
FRIENDLY LOCAL RAMP METERING CONTROL SYSTEM**

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FINAL REPORT

June 2023

This material is based upon work supported by the Federal Highway Administration under the State Planning and Research program. Any opinions, findings, and conclusions or recommendations expressed in this publication are those of the author(s) and do not necessarily reflect the views of the Federal Highway Administration or the Maryland Department of Transportation. This report does not constitute a standard, specification, or regulation.

TECHNICAL REPORT DOCUMENTATION PAGE

1. Report No. MD-23-SHA/ MSU/ 6-1	2. Government Accession No. (n/a)	3. Recipient's Catalog No. (n/a)	
4. Title and Subtitle Design and Demonstration of an Arterial-friendly Local Ramp Metering Control System		5. Report Date June 2023	
		6. Performing Organization Code DUNS Number: 879941318 EIN: 52-6002033	
7. Author(s) Zemian Ke, Jiachao Liu, Qiling Zou, Weiran Yao, Yi Liu, D.Eng. https://orcid.org/0000-0002-6861-2914 Sean Qian, Ph.D. https://orcid.org/0000-0001-8716-8989		8. Performing Organization Report No. (n/a)	
9. Performing Organization Name and Address Morgan State University 1700 E Cold Spring Lane Baltimore Maryland 21251		10. Work Unit No.	
		11. Contract or Grant No. SHA/MSU/6-1	
12. Sponsoring Agency Name and Address Maryland Department of Transportation (SPR) State Highway Administration Office of Policy & Research 707 North Calvert Street Baltimore MD 21202		13. Type of Report and Period Covered SHA/MSU/6-1 Final Report (April 2021- May 2023*) *This is the performing period.	
		14. Sponsoring Agency Code (7120) STMD - MDOT/SHA	
15. Supplementary Notes			
16. Abstract This project aims to develop, assess, and optimize control strategies for ramp metering and local signal synchronization in Maryland's Transportation Systems Management and Operations (TSMO) 1 system (I-70 corridor east of Baltimore, MD). The methodology and mesoscopic simulation model can be generally applicable to other networks and TSMO systems. The network was calibrated using multi-source multi-class traffic data, which has a satisfactory accuracy to reproduce actual traffic conditions. Tests on various scenarios of demand level, control strategies, and incident occurrence show that the local signal synchronization (LSC) consistently performs well in terms of achieving a greater reduction in average travel time, vehicle miles traveled (VMT) and vehicle hours traveled (VHT), and ensuring a good balance of vehicle delay on both arterials and downstream highway segments. The recommendation to Maryland Department of Transportation State Highway Administration (MDOT SHA) is to consider implementing an LSC control strategy to coordinate between ramp metering and localized signal controls to achieve best performance and ensure equity.			
17. Key Words Ramp metering, coordinated control, mesoscopic traffic flow, multi-source data calibration, system-level performance		18. Distribution Statement This document is available from the Research Division upon request.	
19. Security Classif. (of this report) None	20. Security Classif. (of this page) None	21. No. of Pages 39	22. Price \$150,000.00

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Executive Summary

This project aims to develop, assess, and optimize control strategies for ramp metering and local signal synchronization in Maryland's Transportation Systems Management and Operations (TSMO) 1 system (I-70 corridor east of Baltimore, MD). This is done through developing a mesoscopic, high-granular, simulation-based dynamic network model for Baltimore regional networks, which enables measure system-level and local-level performance. Those control strategies can be applied to typical weekdays to mitigate highway congestion without compromising traffic conditions on surface streets. In addition, coupled with ahead-of-the-curve traffic prediction, those control strategies can be engaged proactively in response to non-recurrent traffic conditions.

A computationally efficient mesoscopic network simulation tool is constructed incorporating a signal control module for coordinated signalized intersections and ramp metering. One run of over 250,000 vehicles across 15,376 origin-destination O-D pairs, 1,509 links, and 775 nodes take less than three minutes on a regular Intel i-5 desktop computer. In addition, this network model can be generally applicable to evaluate and optimize other traffic management strategies, such as lane control, pricing, information provision, queue warning, etc. This would help the Maryland Department of Transportation State Highway Administration (MDOT SHA) with other Intelligent Transportation System (ITS) related projects for TSMO 1 system.

The dynamic network model is calibrated by a state-of-art data-driven calibration framework using multi-source, multi-class data collected from different traffic sensing systems. The result demonstrates the calibrated model has a satisfactory accuracy to reproduce actual traffic conditions.

Two control strategies, ALINEA and local signal synchronization (LSC), are implemented and tested to control metering rates at two most prominent ramp locations along the I-70 corridor. The goals are minimizing system-level congestion and ensuring equity among highways and arterials. Various scenarios with different demand levels, control strategies and incident occurrence are generated to examine the effectiveness and robustness of the proposed control methods.

The main finding of this project is that the LSC method consistently outperforms ALINEA in terms of achieving a greater reduction in average travel time, vehicle miles traveled (VMT), and vehicle hours traveled (VHT). LSC also ensures a good balance of vehicle delay on both ramps and immediate downstream highway segments.

It is recommended to SHA to consider performing coordination among ramp metering and localized signal control to achieve the best performance and ensure equity. The LSC method has a stable performance under recurrent congestion and non-recurrent traffic impacts. It can be proactively engaged with ahead-of-the-curve traffic prediction under non-recurrent incidents that impact the immediate downstream highway segments of ramps.

1. Introduction

Operating a joint network of highways and arterial streets in real-time is challenging. The main challenges are twofold. Highways and arterials are highly inter-dependent but may have their own operational strategies and systems that do not necessarily synchronize. As a result, traffic queues can spillover from highways to arterials, or the other way around, leading to substantial congestion that worsens the overall system performance. Coordinating the signal control system on arterials and ramp metering control on ramps to/from highways are one key to mitigating such congestion. In addition, most signal or ramp metering systems deal with recurrent traffic congestion or normal traffic conditions. They can alleviate queues locally to some extent under non-recurrent congestion (being responsive or reactive) but are not designed to prevent queuing from the occurrence of incidents (being predictive) nor mitigate congestion for the joint network. To this end, managing traffic predictively (or proactively) and coordinating ramp metering and street signals among all relevant highway on-ramps/off-ramps can effectively improve the joint network performance.

Transportation Systems Management and Operations refers to a set of strategies that could be utilized to mitigate system-level congestion, particularly non-recurrent traffic impacts, such as information provision, signalization, and access control. Though TSMO are technically available to practitioners, but what time and what strategy to engage remains unknown. Being predictive and proactive, and coordinating among all control strategies (e.g., street signals and ramp metering jointly), is the key to effective management of network-level traffic. Proactive operational management is highly dependent on accurate real-time traffic data and swift real-time traffic prediction.

This research project aims to integrate solutions to the two problems into a fully scalable TSMO system: ahead-of-curve prediction and system-level signal and ramp metering coordination. The former was previously addressed by [1], where we propose theories, models, and algorithms of machine learning to predict traffic patterns in real time and identify non-recurrent patterns. Provided with advanced prediction, signal timing plans can be adjusted ahead of severe congestion (recurrent or non-recurrent) to favor foreseeable flow streams that become dominant on certain streets or routes. To this end, we develop models and test solutions to optimize the timing plans for both ramp metering and street signals in the TSMO system. Prediction and operational strategies are intimately coupled. The prediction will be made by a machine that learns not only historical traffic patterns, but also real-time data (possibly from multiple sources). Operational strategies are made and updated in real-time to achieve management goals (e.g., minimization of total travel time) as a result of ahead-of-curve prediction of network impacts. In particular, acknowledging the effectiveness of the ahead-of-curve prediction, the research focuses on the system-level signal and ramp metering coordination for system-level performance improvement: fuse multiple data sources related to highways and local street/intersections; develop an efficient network-level modeling framework enabled and validated by multi-source data; make real-time optimal signal plans and ramp metering plans; and finally quantify the network benefits of operational strategies to improve mobility/safety. The project demonstrates the effectiveness and replicability of the models and algorithms in Maryland's TSMO 1 system.

2. Literature Review

This section presents a review of prior work on transportation network flow models and how ramp metering and signal timing control are incorporated into the network loading models. State-of-the-art control schemes for ramp metering and signal timing are also summarized.

2.1 Network Traffic Flow Model

In traffic flow models, transportation networks are represented by directed graphs. The links of a graph represent major roadway segments. The nodes of a graph are placed at locations where a major change in road geometry occurs (e.g., on-ramps and off-ramps, merge/diverge, intersections, etc.), or to enforce boundary conditions such as origin-destination (OD) demand and control schemes such as signal timing and ramp metering [2].

2.1.1 Transportation Network Modeling

In mesoscopic traffic simulation, traffic flow is first quantized into vehicle packets [3]. A small loading interval (e.g., 5 seconds) is set and vehicles are released from origin nodes. At the beginning of each interval, the vehicles are loaded through the network according to the evolution rules defined by link and node models, and vehicles are kept moving until all vehicles reach their destinations. The core components of network flow models, or dynamic traffic assignment (DTA), are thus link models, node models, and travelers' route choice models. To approximate various real-world roadway and driving scenarios, abundant research has been conducted for the three core models below.

Link Model: Given supply and demand of each link at time step t , link models determine receiving and sending flow and move vehicles through each link in the traffic network.

Point queue (PQ) models [4, 5] place the queue at the downstream end of the link which occupies no physical space but conceptually holds vehicles back to represent any congestion delay on the link [2]. PQ discharges vehicles at a maximum rate and the receiving flow is a constant which represents the maximum in-flow rate. PQ is often used to model virtual (un)loading links connected to origin and destination nodes.

Spatial queue (SQ) models [6] add a gate on receiving flow to reflect the finite space on the link. Queue spillover occurs at critical density, i.e., at that time no vehicles can enter the link. The sending flow for SQ is calculated in the same way as for PQ model. SQ simulates the scenario where all vehicles in a queue move together. SQ can be used to model short links as spatiotemporal evolution of queue spillback along the link is ignored by the model.

Cell transmission model (CTM) [7] is an explicit solution to Lighthill-Whitham-Richards (LWR) hydrodynamic traffic flow model using Godunov's scheme [8, 9]. Time is discretized into intervals of length Δt and links are divided into cells of length $\Delta x \leq [v_f \Delta t]$ (where v_f is the free-flow speed of a link) which ensures a vehicle can travel through a cell in one time step under free-flow traffic conditions. The queues are placed at each cell along the link so the spatiotemporal evolution of queue spillback can be modeled.

Link queue (LQ) [10] models each link in the graph as a cell while still continuously approximating the kinematic wave model on a road network. CTM and LQ are often used for modeling flow evolution for major roadways in the network.

Link transmission model (LTM) [11, 12] uses the Newell-Daganzo method to directly calculate sending and receiving flows of each link. Instead of tracking the states of cells within links in CTM, LTM stores the link cumulative curves and calculates the outflow at the ends of the links using the forward and backward prevailing traffic states determined by link fundamental diagram. A stochastic network loading model called double queue (DQ [13, 14]) is also developed as a probabilistic extension of LTM.

Node Model: A node model is a predefined function that computes the resulting flow on each connecting pair while satisfying several constraints and principles [2] which respect route choices, first-in-first-out (FIFO), and invariance principles, etc.

FWJ node model [15, 16, 17] is one example of junction flux function which computes the flux of any upstream link to any downstream link using the minimum of weighted average sending and receiving flow weighted by turning portions. A general node model which handles multiple upstream and downstream links was proposed by [18] the virtual demand which represents the maximum possible outflow rate and virtual supply which represents the maximum possible receiving flow is used instead of actual demand and supply. These two general node models contain link-in-series, diverge, and merge nodes as a special case, and can model general uncontrolled-competition intersections [19].

Complex link and node models can also represent signal-controlled intersections, stop/yield-controlled intersections [20], roundabouts, ramp metering, and so forth. The integration of signal-controlled intersections and ramp metering are summarized in Section 2.1.2 and 2.1.3.

Route Choice Model: Route choice models convert origin-destination (OD) demand into time-dependent path flows. Popular route choice models include dynamic user equilibrium [21, 22], dynamic system optimal [23, 24], adaptive routing, hybrid models [25], and discrete and logic choice models [26, 19, 27, 28]. For non-recurrent traffic conditions, behavior models that characterize traveler's behavior changes after incidents [29, 30] and prediction-correction models [31] are often built to simulate the time-dependent diverted traffic flow under pre-defined incident scenarios. The research gap lies in modeling route choices under unplanned incidents and providing a reasonable goodness of fit to field traffic data.

2.1.2 Ramp Metering Integration in Network Modeling

The most common approach to model ramps with signal control is by supply-demand approach [32]. For a freeway on-ramp with a meter, the ramp metering rate ($0 \leq r(k) \leq 1$) is the ratio of metered flow rate over the on-ramp full flow capacity C , which clips the demand of upstream links [33, 34, 35, 36, 37, 38]. An alternative approach applies metering rate directly on the outflow that would leave a cell in absence of ramp metering [39]. The metering rate $r(k)$ is given by a ramp controller (e.g., fixed time [40], local [41], coordinated [42]) and updated depending on traffic conditions [43]. In [44], the state-space model for each segment is

formulated as a subsystem with a discrete-time stochastic state-space model linear to the vector of ramp metering rates produced by the respective controller.

2.1.3 Signal-Controlled Intersection in Network Modeling

For a signal-controlled intersection, each turning movement is represented as a separate link model and an intersection node model permits a combination of movements that receive the right-of-way with a gate on the upstream link demands [32, 45, 46]. A pre-timed signal timing document (or given by a controller in real-time), defines the group of permissible vehicle movements, cycle length, green split, and offset, and is then used by the intersection node as model input. A network traffic assignment with integrating signal control and path-based signal was presented in [47, 48]. A set of experiments was designed to compare the network performance under the path-based coordination scheme with no coordination and arterial-based coordination. In [45, 46], the signal control splits given by a controller is applied to the intersection cells to reduce maximum flow capacity. A linear DTA with signal control was then developed which obtains system-optimal flows as well as the lowest possible emission. A joint dynamic traffic routing and adaptive signal control model is proposed in [49]. The control strategy is tested and analyzed by microscopic traffic simulation with signalized intersections under different levels of demand. [50] optimized the timing of signalized intersections for each rate to eliminate the impacts of sub-optimal signal timing parameters on network performance. It should be noted that due to the characteristics of gated signals at intersections, the network dynamics is often rendered into a nonlinear model with discrete states and inputs [51]. Continuous relaxations [52, 53, 54, 55, 56], surrogate methods [57, 58], and decomposed models [59] were proposed to convert the system dynamics to continuous regime or to a stack of smaller optimization problems.

2.2 Integrating Ramp Metering and Intersection Signal Control

Ramp metering [60] and intersection signal control strategies can be categorized into pre-timed or traffic-responsive methods [35]. Pre-timed signal timing plans [40] are optimized for particular times of the day, or a typical day of week and holidays based on constant historical traffic. Traffic-responsive control strategies can be further classified as local and coordinated [60]. Local strategies make use of traffic measurements in the vicinity of a ramp or intersection to optimize ramp metering values or splits, offsets, and cycle of signal timing plan. Coordinated strategies make use of measurements from an entire region of the network to control and synchronize all metered ramps and signalized intersections. Local strategies include rule-based controllers such as proportional-integral-derivative (PID) controller [41], neural network or fuzzy-logic based approaches [61], and reinforcement learning [62, 63]. Coordinated strategies involve interactions among signals and metered ramps through network flow models. Optimal control strategies or model-predictive control (MPC) are often used. Most Traffic Management Centers in the U.S. operate a coordinated signal system that relies on historically generated signal timing plans, coupled with real-time technology to manage day-to-day operations on the local network [1].

2.2.1 Ramp Metering Control

Fixed-time ramp metering strategies are optimized off-line for particular times-of-day with constant historical traffic. Linear programming or quadratic programming problems [40, 64, 65] were formulated to solve for static on-ramp volumes which maximize the number of served

vehicles while avoiding traffic congestion on the mainline. Due to the absence of real-time measurements, pre-timed ramp metering strategies cannot adapt to real-time traffic states (e.g., non-recurrent demand, incidents, etc.) and may lead to congestion or underutilization of the freeway [35].

The most commonly used traffic-responsive approach for local ramp metering control is the feedback ALINEA controller [41, 66]. ALINEA is a feedback controller to track the difference between desired down-stream occupancy (typically the critical occupancy) and current occupancy with ramp metering rate. Neural network [67] or fuzzy-logic based [61] methods are also applied. For coordinated ramp metering control strategies, optimal control or MPC [68, 35, 69, 70] which embed a network flow model with ramp metering into the optimization are proposed.

Recently, reinforcement learning (RL) methods are used for local and coordinated ramp metering control [71, 72, 73, 74]. A simulation environment with ramp metering control is built with system states, control inputs, and rewards are defined beforehand. A neural network is updated to approximate the optimal control policy [63, 75, 76] which maps the system states to the control inputs to maximize the cumulative future rewards. However, the effectiveness of RL methods for real-world applications is often questioned, since there is a lack of a risk-free traffic environment for RL to exercise trial-and-error considering RL's low sample efficiency [77, 78]. In addition, RL algorithms make assumptions on system dynamics that may not necessarily align with ground truth, they may take quite long time to converge in practice. This prevents the deployment of RL in ramp metering practice.

2.2.2 Signalized Intersection Control

Classic traffic signal control methods include Webster method [79], GreenWave [80], MaxBand [81], SOTL [82], Max pressure [83], SCOOT [84], etc. A detailed review of these methods can be found in [85]. These methods should be taken into comparison as baselines for MPC or RL methods. For coordinated signal timing control, several dynamic traffic assignment models with signal control [86, 87, 88, 89] have been proposed in the literature. Most of them are formulated as a mixed-integer programming (MIP) program due to the discrete nature of system states and control inputs. Continuous relaxation to the optimization problems are later presented [52, 53, 54, 55, 56]. As an alternative, multi-agent reinforcement learning (MARL) approaches [90, 91] are recently applied to scale coordinated signalized intersection control to large-scale network [92].

A fully decentralized multi-agent actor-critic algorithm for adaptive traffic signal control is presented in [93]. [94] tackles the problem of multi-intersection traffic signal control, especially for large-scale networks, based on RL techniques and transportation theories. The results demonstrate optimality and sample efficiency in a real-world scenario with 2,510 traffic lights in Manhattan, New York City.

2.2.3 Integrated Corridor Control: Local Synchronization

Traffic corridor control optimizes traffic performances in both motorways and urban roads, typically integrating ramp metering control at the motorway entrances with signal control at road intersections [95]. Jointly optimizing both sub-systems in MPC is essentially hard. [36]

proposed a solution by integrating actuated signal control and ALINEA through local synchronization. The framework controls ramp metering rate by ALINEA, but the meter is switched off when the intersection was congested and queue-overwrite was needed. Actuated control is used for signalized intersection with the maximum green of each phase adjusted according to the real-time traffic states. Similarly, in [96], ramp metering is controlled by UP ALINEA with queue-overwrite and an interchange signal optimization node which takes into account the meter rate and on-ramp queue length are solved to obtain green duration for each movement. A local synchronization traffic control scheme is proposed to manage queues at those critical locations through coordination of neighboring intersection traffic signals and freeway on-ramp meters.

A decomposed corridor control framework is developed in [97] which features a linear programming algorithm for coordination of a freeway entrance ramp metering and an arterial intersection signal. This framework is comprised of three components: (1) intersection signal timing optimization which minimizes the gap between demand and supply of all movements, (2) a ramp metering control using ALINEA, and (3) coordination strategy of the two traffic control systems which adjust parameters in the objective function of intersection signal timing optimization. The framework is tested at Freeway SR87 near Taylor and analysis demonstrates the effectiveness of the approach with a net delay reduction by 7%.

3. Research Gaps and Tasks

Based on the literature review, the main research gaps lie in:

- The dynamic network models integrating both ramp metering and local signalization exist but are in lack of theories and models to be calibrated with large-scale multi-source data. Those data sets become increasingly available, for example, 24/7 traffic counts, traffic speeds, weather conditions, vehicle classifications, incidents, and Waze, which could help better understand the dynamic O-D flow and travel behavior under unplanned incidents.
- The dynamic network models usually consider only standard passenger cars without explicitly modeling trucks, though the impact of trucks can be tremendous, particularly under non-recurrent incidents. Traffic data by vehicle classification can be used to better understand the travel behavior and traffic flow by cars and trucks, separately. Therefore, information dissemination and signal control may target a specific vehicle class to improve system efficiency.
- Most of models for synchronizing ramp metering and local signalization are designed for a few adjacent intersections surrounding a ramp. The network impact of signal synchronization at the level of multiple ramps across multiple highways are not explicitly modeled. This is particularly important for managing a regional network, e.g., a TSMO system for a corridor or a network.
- Most of control strategies for synchronizing ramp metering and local signalization are responsive or reactive. Control strategies reactive to detected incidents or real-time traffic flow, which could be too late to gain system improvement once the congestion is already occurring. The best way is to design control strategies in a predictive manner. Traffic can

be predicted for each roadway segment 30 minutes in advance. Thus, engaging optimal control is designed to prevent substantial queuing proactively.

In view of these research gaps, a recommended proposal is to develop and assess the timing plans for both ramp metering and street signals to proactively prevent queuing, stemming from either recurrent congestion or from the occurrence of incidents. Instead of explicitly modeling microscopic traffic flow dynamics for on-ramp and off-ramp impacts, the integrated ramp metering and signal control will be made based on a path-based dynamic network model which enables predictions of network impacts of recurrent and non-recurrent traffic through explicitly modeling path-level travel behavior. The architecture learns not only historical traffic patterns but also has the potential to be fine-tuned with real-time data.

The project is divided into four major tasks:

Task 1: Identify and Process (pre-COVID) Various Data Sources for in-Depth Data Analytics and System Control

The following data are collected, processed, and integrated for network modeling and further development of control strategies in the TSMO 1 system, as shown in Figure 1:

- Transportation network data (GIS model) for the TSMO 1 area.
- Traffic counts by vehicle classes on local streets, intersections, and highways in the TSMO 1 area.
- Traffic speed data for highways in the region and major arterials within the TSMO 1 area.
- Existing signal timing schemes for selected intersections and planned ramp metering schemes.
- Management goals in the TSMO 1 area, such as queue limits on on-ramp and off-ramps, as well as on local streets.
- Historical incident data, including the geographical scope of the closures, lane closure configurations, crashes, and past events that substantially influence traffic in the TSMO 1 area.

Task 2: Establish a Dynamic Network Model for the TSMO 1 System

An open-source mesoscopic network analysis tool, MAC-POSTS (Mobility Data Analytics Center - Prediction, Optimization, and Simulation toolkit for Transportation Systems)¹, developed by Mobility Data Analytics Center (MAC) at Carnegie Mellon University (CMU) is used to simulate the dynamic traffic flows over time in the TSMO 1 area. The TSMO 1 regional network, together with the construction plans and/or incidents, will be coded into MAC-POSTS. A dynamic network model for TSMO 1 is established that provides estimated 5-minute origin-destination demand among all street segments that vary by time of day. The travel demands in the area are carefully calibrated using multi-day data sets collected in Task 1. With the estimated demand, the network model is then able to replicate the close-to-real-world traffic dynamics. It also has the capacity to model dynamic traffic evolution with the consideration of any other travel control and traffic demand management strategies than ramp metering. This model adopts state-of-the-art traffic models and is much more computationally efficient than other microscopic models that are extremely labor-intensive to establish. It should be noted that this dynamic network model can be leveraged for MDOT to make optimal decisions on capital

investment, incident management, traffic control, queue warnings, traveler advisory, and other ITS strategies in general.

Task 3: Develop Control Strategies for Ramp Metering and Local Signal Synchronization

Based on the dynamic network work developed in Task 2, two control strategies i.e., ALINEA and local signal synchronization (LSC), are used to control metering rates at different meters along the corridor and related arterials signals to minimize system-level congestion while ensuring equity among highways and arterials. While ALINEA operates on each ramp independently, the LSC takes into account the coordination of ramp meters and local signalized intersections.

Task 4: Evaluate the Effectiveness of Optimal Corridor Control for Each Scenario

This task evaluates the TSMO 1 system performance before and after the deployment of corridor control under different scenarios. The performance metrics include total traffic delay, average travel time, emissions, energy use, vehicle-miles traveled, congestion attributed to highway or local roads, etc. This will be completed in a simulation environment but can serve as a benchmark of control system performance before field deployment in the future.

The rest of the report details the methodologies to complete these tasks and discusses the results and findings.



Figure 1. Location of TSMO 1 System

4. Data collection and processing

TSMO is the State Highway Administration (SHA)'s integrated approach to planning, engineering, operating, and maintaining existing facilities to maximize their full-service potential, and ultimately improve the safety, security, and reliability of the transportation network [98]. The TSMO 1 system, located in the western region of Baltimore, MD, encompasses two main east-west highway corridors: I-70 and US-40, as shown in Figure 1. Particularly, this area has multiple locations of signal control and ramp metering control points and the TSMO program provides sufficient data and infrastructure resources as a testbed for implementing/testing integrated corridor control strategies.

This section briefly discusses the multiple data sources used in this project, including network topological data, traffic count data, traffic speed data, signal timing plans, and incident data.

4.1 Network Description

To build the network, data from multiple sources is used and fused together. The original network topological data is from INRIX [99], while the link geometry information is acquired from Whitman, Requardt & Associates (WRA) [100] as well as Topologically Integrated Geographic Encoding and Referencees (TIGER) census road shapefiles [101]. The number of lanes for the roads is extracted from Google Maps [102]. To better model the traffic dynamics within this area, we expand the modeling area by incorporating the surrounding areas which can also generate traffic demand using the TSMO 1 system.

We further consolidate the network in order to make it more robust for dynamic traffic simulation and alleviate the computation complexity [103]. The original network data is trimmed to ensure there are no isolated nodes and links. In addition, some neighboring links with small lengths and the same speed limit are further combined, which can substantially reduce the network size. The OD connectivity is also examined in order to correctly estimate OD demand. Figure 2 depicts a part of the network before and after the consolidation.

The final network model used for the subsequent analyses contains 1,509 links, 775 nodes, 124 origins/destinations, and 15,376 OD pairs, as shown in Figure 3.



(a) Before consolidation



(b) After consolidation

Figure 2. Illustration of Network Consolidation (blue line: link, green dot: node)



Figure 3. *An Overview of the TSMO Network*

4.2 Traffic Counts

Traffic count data represents the vehicle counts passing by a certain location, and it is usually collected by loop detectors, tubes, or manual counting. In this project, the count data is provided by the MDOT. However, due to the scarcity of count data and in order to better calibrate the model, data was collected from the available counts from 2017 to 2021, which include both pre-COVID and COVID traffic conditions. In order to estimate a baseline (on a recurrent traffic day) travel demand, the count data excludes weekends, holidays, as well as any days affected by incidents such as accidents, road closures, or hazardous weather conditions.

The count data is carefully examined, cleaned, and matched to the links in the transportation network. Two vehicle types, i.e., cars and trucks, are counted separately in the data, which represent smaller private or ride-hailing vehicles, and larger freight trucks, respectively. In total, there are 153 locations with valid car and truck volumes, as shown in Figure 4.

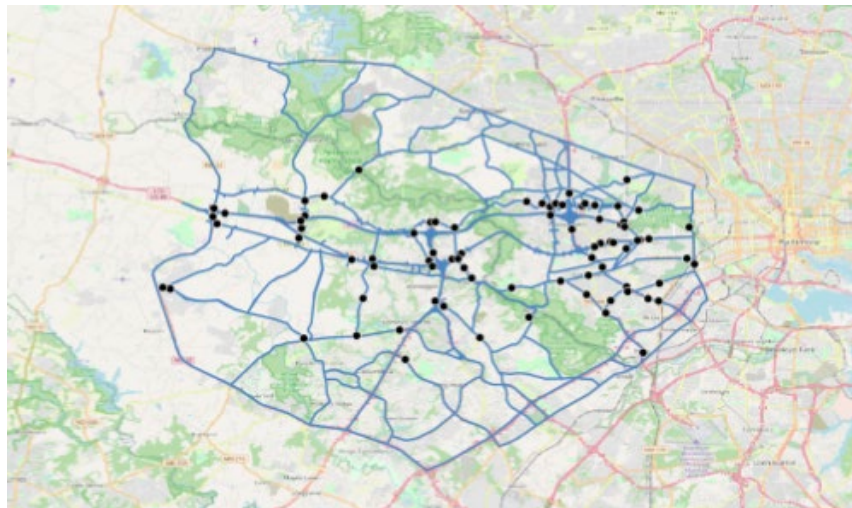


Figure 4. *An overview of the traffic count locations*

4.3 Traffic Speed Data

Traffic speed data is provided by INRIX and obtained from Regional Integrated Transportation Information System (RITIS) [104] for the weekdays during 04/01/2017-12/31/2017. Speeds of different vehicle types are measured separately, and hence both passenger car speeds and freight truck speeds are available. All speed data is measured every five minutes of each day, and we average the data for different days in 2019 and aggregate the data to 15-minute intervals. There are a total of 537 links with valid car and truck speed measurements, as shown in Figure 5.

4.4 Other Data

Besides the traffic counts and traffic speed data, existing signal time plan was also obtained for ramps and local intersections of interest from SHA, which can be integrated into the dynamic network model. Meanwhile, the incident data was acquired from Waze [105], archived by SHA, which includes accidents, road closures, or hazardous weather conditions within this area. The incident data is used to distinguish non-recurrent traffic data from recurrent one and thus identify the typical non-recurrent traffic flow patterns.



Figure 5. *An overview of the Speed Data (links with observed speed data are marked in red)*

5. Dynamic Network Modeling

This section describes traffic dynamics modeling for the TSMO 1 network.

5.1 Mesoscopic Multi-Class Traffic Flow Model

In this project, the traffic dynamics in the region are simulated in high spatio-temporal resolutions. The MAC at CMU develops an open-source multi-class dynamic network modeling tool, MAC-POSTS, which is capable of simulating network-wide traffic dynamics for any general networks consisting of freeways, arterials, and local streets [19]. MAC-POSTS adopts the state-of-art mesoscopic traffic flow model and can scale up to regional-level transportation networks. MAC-POSTS can be calibrated to replicate real-world traffic conditions and predict the impact of different traffic scenarios, such as tolling, work zones, events, and incidents.

For modeling the heterogeneous vehicle flow on links, MAC-POSTS adopts a multi-class traffic flow model proposed in [106], which can model the flow dynamics consisting of multiple classes of vehicles with distinct flow characteristics. It pragmatically generalizes the CTM to multi-class heterogeneous vehicle flow. It includes the concept “physical space split” for each class, which is the fraction of physical space that each vehicle class occupies and uses to progress. Then the “perceived equivalent density” of each class is calculated, representing the equivalent density perceived by some vehicle class, if converting all other class vehicles to this class based on the space they occupied. At each loading time interval, vehicles move through cells following the relations between upstream demand and downstream supply computed using the “physical space split,” and “perceived equivalent density,” as well as the fundamental diagram of each class. The main feature of this multi-class flow model is that it encapsulates three mixed flow regimes: one class can overtake the other class under free flow, overtaking occurs restrictively under semi-congestion, and no overtaking can occur under congestion. More details can be found in [106].

As for a node model for vehicular flow evolution through junctions, MAC-POSTS uses a relaxed version of the general node model introduced by [15]. For junction j , denote the set of all upstream links by $A_{\rightarrow j}$, and the set of all downstream links by $A_{j \rightarrow}$. Also, denote the turning proportion from any upstream link $a \in A_{\rightarrow j}$ to any downstream link $b \in A_{j \rightarrow}$ at time t by $\psi_{a \rightarrow b}(t)$, where $\sum_{b \in A_{j \rightarrow}} \psi_{a \rightarrow b}(t) = 1, \forall a \in A_{\rightarrow j}$. The flux from any upstream link $a \in A_{\rightarrow j}$ to downstream link $b \in A_{j \rightarrow}$:

$$q_{a \rightarrow b} = \min\{d_a(t)\psi_{a \rightarrow b}(t), s_b(t) \frac{d_a(t)\psi_{a \rightarrow b}(t)}{\sum_{\alpha \in A_{\rightarrow j}} d_\alpha(t)\psi_{\alpha \rightarrow b}(t)}\} \quad (1)$$

Where for any link a , the link demand $d_a(t)$ and supply $s_a(t)$ can also be computed for deciding the number of vehicles to be moved through the junctions.

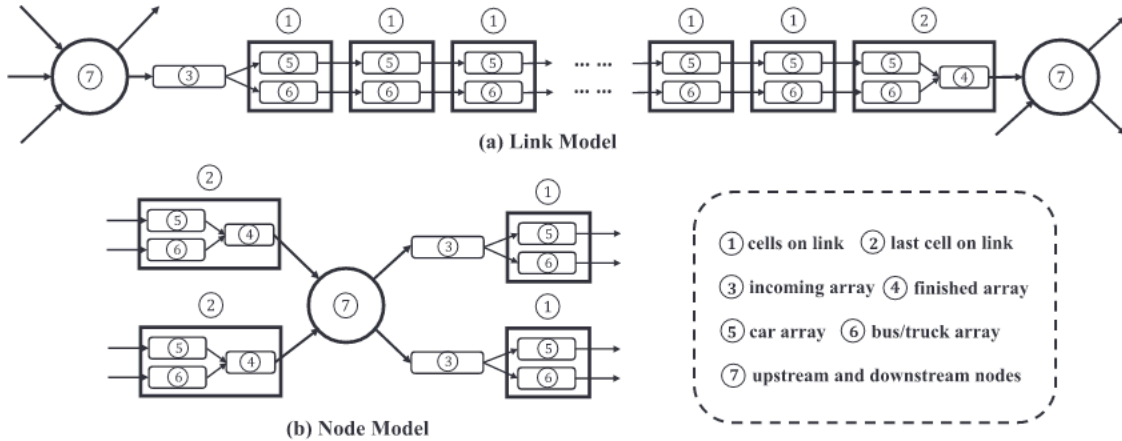


Figure 6. Implementation of link and node models

Note that the model successfully includes the effect of queuing and spill-back in the dynamic network loading. Figure 6 depicts the implementation of the above link and node models, where the arrows represent how we move different classes of vehicles within the links and among different links through the nodes.

5.2 Signal Control Modeling

To properly account for traffic controls, the flow updating rules for the CTM in the dynamic network model are modified to model the effects of signalized intersections and ramp meters on traffic flows.

5.2.1 Signalized Intersection

In the original CTM, the relation of the flow q and the density k is in the form:

$$q = \min(vk, q_{max}, u(k_j - k)) \quad (2)$$

Where q is the link flow; q_{max} is the saturation flow rate; v is the free flow speed; k is the density; k_j is the jam density; and u is the backward propagation speed.

To model the flow updates at signalized intersections, the major modification is to make the maximum flow q_{max} in Eq.2 time-dependent in accordance with the signal timing.

$$q_{max}(t) = \begin{cases} q_{max}, & t \in \text{green} \\ 0, & \text{otherwise} \end{cases} \quad (3)$$

Where it switches between q_{max} (green phase) and zero, the end cell of an intersection approach will serve as a functioning signal, and the flow dynamics still approximate the kinematic wave model. The traffic at a typical intersection is grouped into movements that go through the conflicting area alternatively during their green time.

Signalized Diverges

The flow diverges at an intersection where the traffic stream on a single link split into left turn, through, or right turn movements. In the modeling, the intersection behind the stop line is virtually enlarged to store the turning vehicles for waiting to be serviced by certain phases.

Denote the end cell C_s^j of a link l_j approaching a signalized intersection, and the flow conservation equation is:

$$n_s(t+1) = \sum_{m=L,R,T} n_s^m(t) + y_{s-1,s}(t) - \sum_{m=L,R,T} y_{s,s+1}^m(t) \quad (4)$$

Where the superscripts of L , R , and T denote the left turn, right turn, and through movement, respectively; $n_s(t)$ denotes the number of vehicles in cell s at time interval t ; $n_s^m(t)$ denotes the number of vehicles under movement m in cell s at time t ; $y_{s-1,s}(t)$ is the number of vehicles moving from cell $s-1$ to cell s at time interval t ; $y_{s,s+1}^m(t)$ is the number of vehicles under movement m moving from cell s to cell $s+1$ at time interval t ; The cell C_{s-1}^j is the preceding cell of C_s^j . The flux into and out of cell C_s^j are:

$$y_{s-1,s}(t+1) = \min\{n_{s-1}(t), Q_{s,max}, \delta_s(N_s(t) - n_s(t))\} \quad (5)$$

$$y_{s,s+1}^m(t+1) = \min\{n_s^m(t), q_{s,max}(t), \delta_{s+1}(N_{s+1}^m(t) - n_{s+1}^m(t))\}, m = L, R, T \quad (6)$$

Where $Q_{s,max}$ is the maximum number of vehicles that can flow into cell s during time interval t ; $N_s(t)$ is the maximum number of vehicles that cell s can hold at time interval t ; $q_{s,max}(t)$ is the maximum number of vehicles that can flow out of cell s during time interval t , which is

controlled by the signal timing plan; $N_{s+1}^m(t)$ is the storage capacity for vehicles under movement m .

Signalized Merges

The flow updating rule for the signalized merge is:

$$n_{s+1}(t+1) = n_{s+1}(t) + y_{s,s+1}(t) - y_{s+1,s+2}(t) \quad (7)$$

Where $s+1$ is the start cell index for the downstream link, i.e., the first cell of the downstream link that receives the stream with cell index of s serviced by the signal. The incoming flux $y_{s,s+1}(t)$ is determined by the signal timing plan:

$$y_{s,s+1}(t) = \min\{n_s(t), q_{s,max}(t), \delta_s(N_s(t) - n_s(t))\} \quad (8)$$

While the outgoing flux $y_{s+1,s+2}$ is computed by the normal CTM cell.

5.2.2 Metered Freeway on-Ramp

Modeling ramp meters only needs to deal with the metering rate R^t at time t . The updating rule at a freeway merge section is as follows:

$$D_R^t = \min(D_R^t, R^t, q_{max}) \quad (9)$$

$$D^t = D_M^t + D_R^t \quad (10)$$

$$S^t = \min(S_M^t, D^t) \quad (11)$$

$$f_M^t = \frac{D_M^t}{D^t} S^t \quad (12)$$

$$f_R^t = \frac{D_R^t}{D^t} S^t \quad (13)$$

Where R^t is the ramp metering rate; D_R^t is the ramp demand at time t ; D^t is the demand upon the beginning cell of the link downstream of the ramp; D_M^t demand on mainline competing with the ramp demand; S_M^t supply of the beginning cell of the downstream link; S^t is the total service flow rate; f_R^t is the outflow from ramp; and f_M^t is the outflow from upstream mainline.

The modification is twofold: (i) the ramp demand to the merge point is bounded not only by actual demand and the flow capacity, but also by the metering rate executed at that time step (Eq.9) (ii) in the overflow or congestion situation, flow from the freeway mainline and the ramp will be distributed to the downstream link proportionally to their relative demand (Eq.11-13).

5.3 Model Calibration

Before applied to practical applications, the dynamic network model needs to be calibrated in order to approximately reproduce the actual traffic conditions. To this end, multiple data sources collected in Section 4 are used and a data-driven calibration framework is adopted to calibrate the model.

5.3.1 Multi-Class Dynamic OD Demand Estimation

This calibration is referred to as the multi-class dynamic OD demand estimation (MCDODE) problem, which aims to estimate the time-dependent vehicle demand for each OD pair in the study period. Different from the traditional dynamic OD demand estimation (DODE) problem, which typically deals with single-class vehicle demand, this MCDODE framework is able to differentiate, and estimate demands for multi-class vehicles, which enables further high-granularity traffic simulation.

The MCDODE is formulated as an optimization problem aiming to estimate travel demand to minimize the discrepancy between the observed data and the simulation results (i.e., traffic count and travel speed). The objective function is as follows:

$$\begin{aligned} \min_{\{q_{car}, q_{truck}\}} \mathcal{L} &= \mathcal{L}_1 + \mathcal{L}_2 + \mathcal{L}_3 + \mathcal{L}_4 \\ &= w_1(|\mathbf{y}'_{car} - \mathbf{y}_{car}|_2^2) + w_2(|\mathbf{y}'_{truck} - \mathbf{y}_{truck}|_2^2) \\ &\quad + w_3(|\mathbf{z}'_{car} - \mathbf{z}_{car}|_2^2) + w_4(|\mathbf{z}'_{truck} - \mathbf{z}_{truck}|_2^2) \end{aligned} \quad (14)$$

Where q_{car} and q_{truck} are the car and truck demands, respectively; \mathbf{y}'_{car} and \mathbf{y}_{car} are the observed and estimated car flows, respectively; \mathbf{y}'_{truck} and \mathbf{y}_{truck} are the observed and estimated truck flows, respectively; \mathbf{z}'_{car} and \mathbf{z}_{car} are the observed and estimated car travel times, respectively; \mathbf{z}'_{truck} and \mathbf{z}_{truck} are the observed and estimated truck travel times, respectively; w_1, w_2, w_3 and w_4 are the weights to balance the five terms in the optimization.

More details of the calibration framework and the computational-graph-based solution method are omitted here, and interested readers are referred to our previous studies [19].

5.3.2 Calibration Results

Simulated traffic conditions are calibrated to match the observed morning peak hour (5 AM - 12 PM) traffic conditions. MAC-POSTS simulates the movements of all vehicles in the studied network with high spatial (around 50 meters) and temporal (5 seconds) resolution. As with the information provided, the assumption is that 60% of cars are adaptive to the traffic information, while 40% of cars and all trucks stick to the pre-scribed routes. Note that MCDODE aims to estimate the baseline travel demand on a recurrent traffic day. As for non-recurrent traffic patterns, time-varying travel demand in the TSMO 1 regional network is assumed to be the same as the baseline scenario. However, route choices of trips during construction/incident will change in response to the level of congestion at various parts of the network evolving by the time of day.

Figure 7 presents the comparison between simulated 5-minute traffic volumes and observed 5-minute traffic volumes, in which the vertical axis is the simulated count, and the horizontal axis is the observed count. The coefficient of determination R^2 , as a measure of goodness of fit, is 0.730 and 0.924, for the car flow and truck flow, respectively. The calibration results are considered to be reasonably well for such a large-scale network, advantageous than many other studies attempting to replicate real-world traffic conditions using network simulations. The discrepancy between the observed flow and simulated flow is attributed to several factors, of which the main reasons are twofold: O-D connectors in the peripheral areas of the network can direct flow from/to using links with volume counters, but they do not necessarily

influence the route choices of traffic across the regional network (this is the case of many dots representing an overly small or overly large observed values); the models of traffic flow dynamic, link/node capacity and route choices can be improved to represent transportation systems more realistically. The former problem can be addressed by carefully generating O-D connector(s) in regards to counter locations, whereas the latter problem can be alleviated by implementing more sophisticated traffic models. Both will be further addressed in future research.

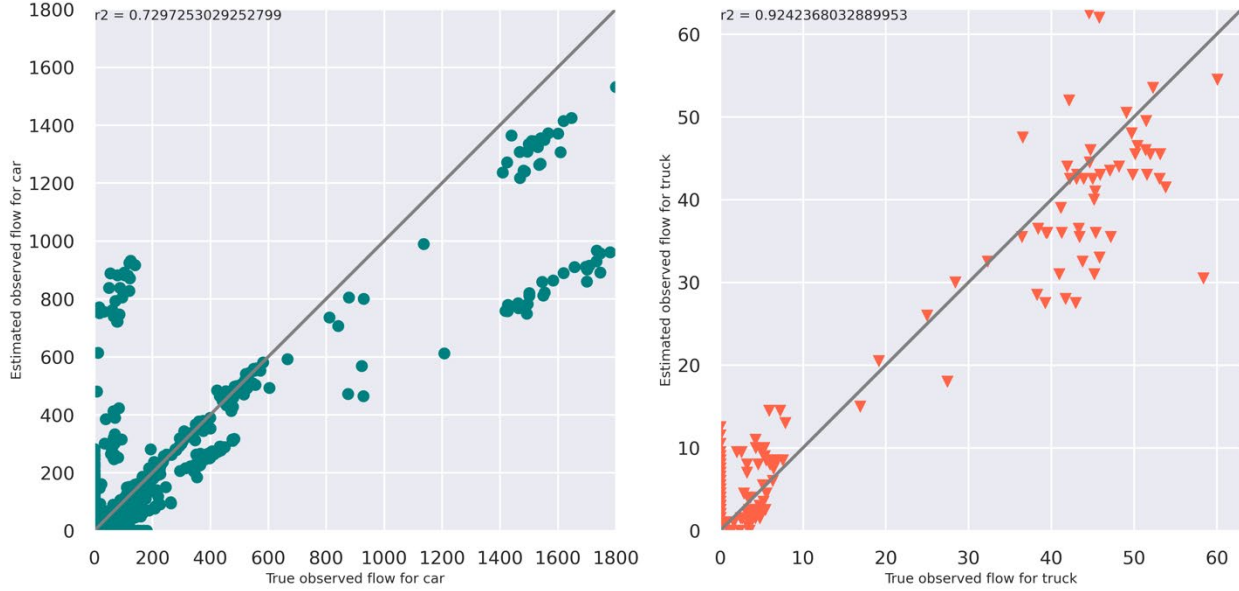


Figure 7. Traffic Count Calibration (left: car count, right: truck count)

Overall, this model shows relatively good performance in capturing the trend of the observed data and this indicates that the proposed regional model can reflect the actual traffic dynamics in the whole TSMO 1 area to some extent. The calibrated model lays the ground for the following development and assessment of different control strategies.

6. Control Strategies

This section describes two control strategies developed to control metering rates at different metering locations along the corridor and related local arterial signals to minimize system-level congestion while ensuring equity among highways and arterials.

6.1 ALINEA

ALINEA is a well-known traffic-responsive metering algorithm [41] which tracks the difference between desired downstream occupancy (typically the critical occupancy) and current occupancy with ramp metering rate. Mathematically, it can be formulated as follows:

$$r(t) = r(t - 1) + K_R(O_c - O_{out}(t)) \quad (15)$$

Where $r(t)$ is the metering rate for the current time step and $r(t - 1)$ is the metering rate in the previous time step, O_c is the target occupancy to be maintained which is usually slightly lower

than the critical density (corresponding to the capacity flow), and $O_{out}(t)$ is the current occupancy. K_R is the only parameter to be adjusted in implementation.

Previous research has shown that ALINEA control can reduce total travel time significantly [60, 107, 108, 109]. But it is for an isolated ramp only, lacking consideration of coordination among ramp meters and local signalized intersections.

6.2 Local Synchronization Control

Congestion that originates at closely spaced highway junctions and intersections, such as freeway interchange areas, could spread and significantly worsen the performance of the entire transportation system. To address this issue, a local synchronization control (LSC) scheme has been developed to coordinate the signal control system on arterials and the ramp metering control on ramps, effectively alleviating congestion.

The LSC scheme effectively manages queues at critical locations by coordinating neighboring intersection traffic signals and freeway on-ramp meters, whenever they are available. Its primary objective is to reduce the influx of traffic into heavily congested sections while increasing the outflow of traffic. By doing so, the scheme prevents queues from developing into the catalysts for gridlock, thereby significantly improving the overall performance of the transportation system.

The LSC scheme is illustrated in Figure 8 [20]. The LSC focuses on closely monitoring traffic operations, specifically the formation of vehicle queues on critical links. These queues, if not promptly addressed, can escalate into local gridlock or even network-wide congestion. When the LSC system identifies the possibility of queue spillback, it takes over the regular traffic operations and implements synchronized control actions aimed at efficiently discharging the queued vehicles while concurrently reducing the inflow of traffic. During this period of LSC activation, the primary objective is to clear the critical queue. Once the queue has been successfully managed and cleared, normal traffic operations are resumed, allowing the system to function as usual.

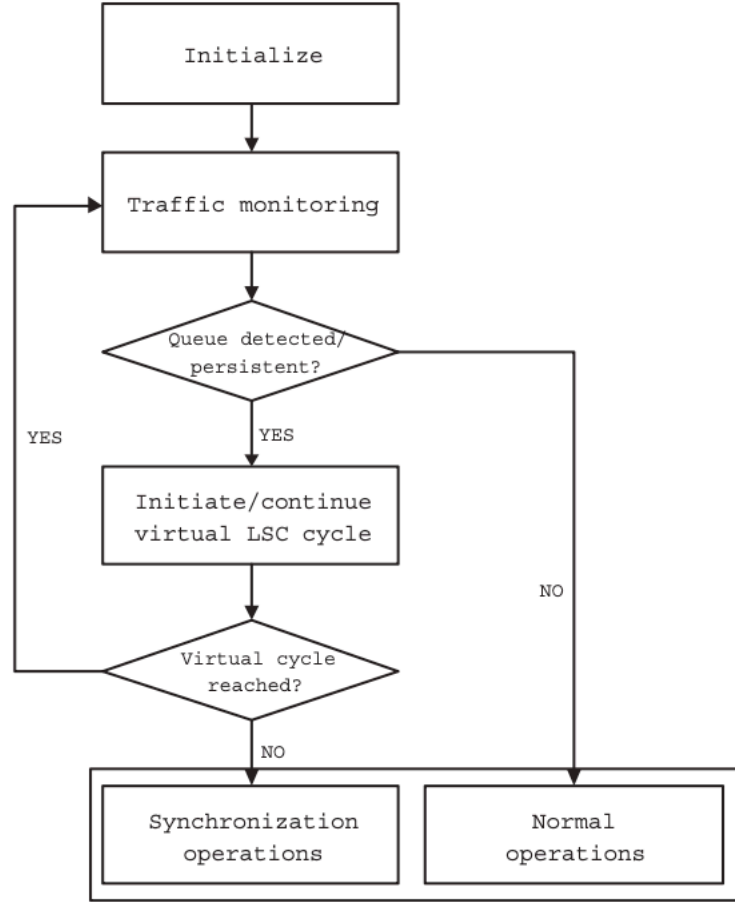


Figure 8. Flowchart of Local Synchronization Control Scheme [20]

Road sections that commonly benefit from synchronization treatment are typically short in length and have significant traffic volumes converging from one or both ends. These sections include on-ramps that are controlled by either on-ramp meters, traffic signals regulating the inflow of traffic, or both. They also encompass off-ramps that lead to signalized intersections, as well as short road segments that connect two consecutive traffic signals. These types of road sections are commonly encountered in freeway interchange areas.

Specifically, for a metered on-ramp, a queue detector is positioned at the upstream end of this on-ramp. When queue spillback is detected, the synchronization operation is activated, implementing the following steps:

- Disabling the current meter: The meter that regulates the flow of vehicles onto the ramp is turned off. This allows ramp traffic to freely merge with the traffic on the freeway, without any restrictions or delays.
- Reducing maximum green time of feeding phases: The duration of the green signal for the traffic signals controlling the lanes that feed into the on-ramp is decreased. By reducing the maximum green time, the aim is to prioritize the discharge of vehicles from the congested ramp, thereby alleviating the queue and preventing further spillback.

These measures work in tandem to synchronize the traffic flow and alleviate congestion on the metered on-ramp. By temporarily suspending the metering process and adjusting the signal timings of the feeding phases, the system aims to efficiently clear the queue and restore smooth traffic operations.

As for the normal operations in Figure 8. it just uses ALINEA to calculate the metering rate.

Overall, the LSC scheme has three important factors:

- Queue detector position: The positioning requires the observation or knowledge of how local congestion evolves during the study period. In the established dynamic network model, queue detection is modeled as tracking the occupancy changes at the detection locations. Particularly, if the traffic flow dynamics are modeled using the CTM, the occupancy will be naturally emulated as the ratio of the number of vehicles to the holding capacity at the location of interest.
- Virtual cycle of the synchronization operation: The virtual cycle specifies the duration of synchronization operations, which continues until the virtual cycle is completed. If the queue persists, another virtual cycle will be initiated, or normal operations will resume if the queue is cleared. The length of the virtual cycle can be determined in conjunction with queue detection and is set equal to the number of intervals required for the queued traffic to traverse the entire congested section in the CTM.
- Adjustment factor of synchronization intensity: The adjustment factor governs the extent to which the affected phases are metered, controlling the duration of the discharging phase increase and the decrease of the feeding phases. Its purpose is to prevent potential negative impacts resulting from an overly aggressive LSC strategy, such as excessively reducing the duration of the feeding phases to their minimum green time.

7. Experiments

This section examines the proposed control strategies on two locations of I-70 highway. Those two locations are selected in regard to their recurrent traffic congestion in the AM peak. The congestion is primarily attributed to merging traffic flow from its on-ramp. Consequently, implementing ramp metering may be able to alleviate the merging conflict and thus has great potential to reduce I-70 congestion. For each location, three cases of calibrated traffic demand are tested: (1) no ramp metering control (i.e., baseline), (2) ALINEA control, and (3) LSC control. Simulations with various demand and lane closure caused by incidents are also conducted to test the effectiveness of control strategies under the occurrence of potential congestion and incidents. Results of different scenarios are summarized, and the best control strategy is identified based on metrics regarding both traffic conditions and environmental impacts.

7.1 Scenarios set-up

Location A is on the merging ramp connecting Marriottsville Rd northbound to I-70 eastbound (shown as the link between node 3165 and 3160 in Figure 9). The local signalized intersection (Resort Road/Marriottsville Road) on the upstream of ramp is also considered.

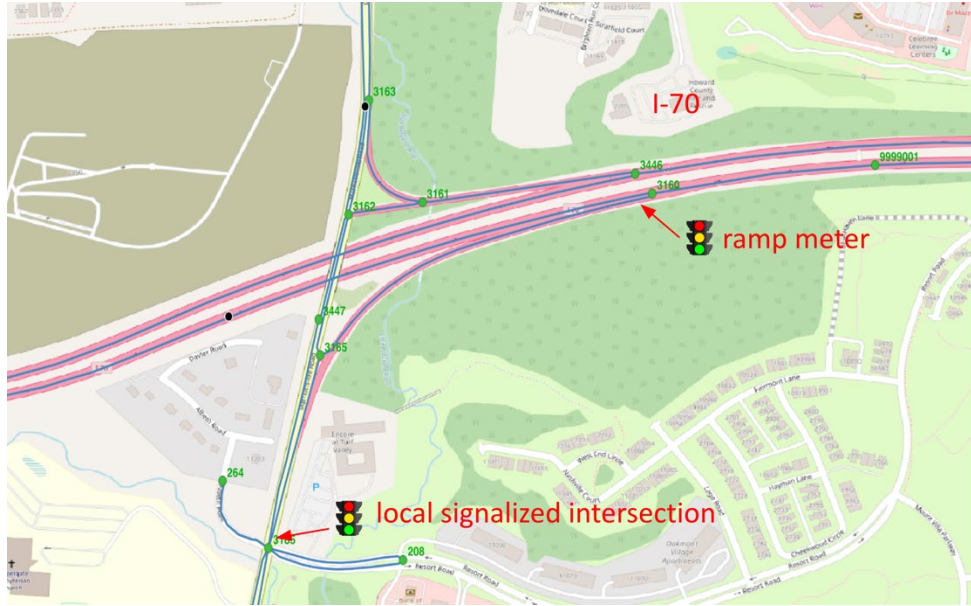


Figure 9. Illustration of the Location A on I-70 Highway

Location B is the ramp connecting US-29 southbound to I-70 eastbound (shown as the link between node 3143 and 3145 in Figure 10). Similarly, a local signalized intersection on its upstream is considered.

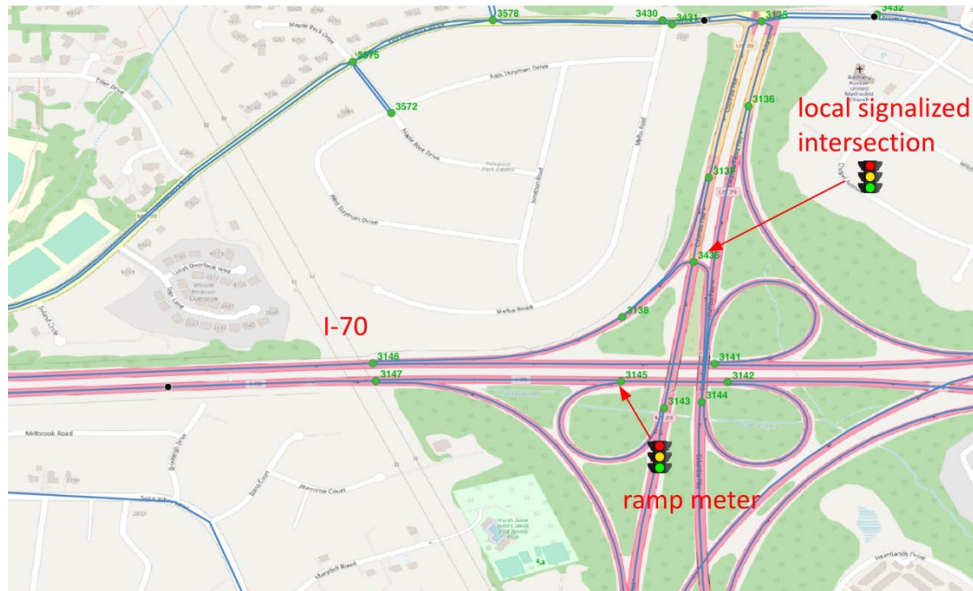


Figure 10. Illustration of Location B on I-70 Highway

For each location, three scenarios are set up to investigate the impact of different ramp metering strategies on local traffic: (1) baseline: no ramp metering control, (2) ALINEA control; and (3) LSC control. In the simulations, 40% of cars stick to the prescribed routes and 60% perform adaptive routing due to the change of traffic conditions, while all trucks use prescribed routes. This is learned as part of the baseline network simulation calibration. The aggregated traffic metrics within the local roads around the controlled ramp and downstream roads are used

For the control strategy with the best performance, five were set up scenarios for each location to test its robustness under different demand levels and a possible occurrence of incidents. Four of the five scenarios use calibrated demand multiplied by scalars ranging from 0.9 to 1.2. The other scenario uses calibrated demand with lane closure caused by hypothetical

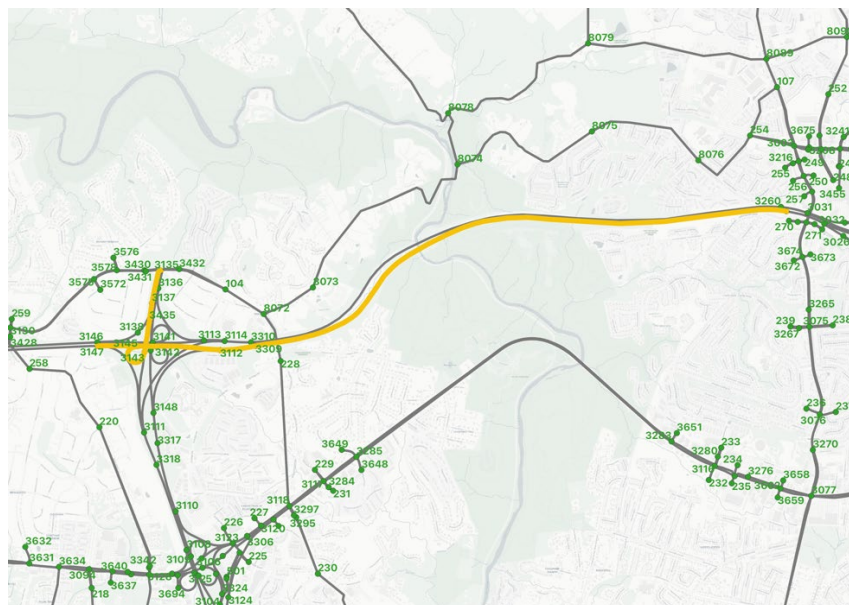


Figure 12. *Selected Links for Location B*

For the control strategy with the best performance, five were set up scenarios for each location to test its robustness under different demand levels and a possible occurrence of incidents. Four of the five scenarios use calibrated demand multiplied by scalars ranging from 0.9 to 1.2. The other scenario uses calibrated demand with lane closure caused by hypothetical

incidents on I-70. The incident occurs on the eastbound I-70 between the intersections Marriottsville Rd/I-70 and US-29/I-70, resulting in the reduction in the number of lanes from 2 down to 1 in the eastbound direction from 7:50 AM to 8:20 AM and the lane reopens after 8:20 AM.

7.2 Results of Scenarios with Calibrated Demand

Tables 1 and 2 present the aggregated metrics of different scenarios with the calibrated demand. The evaluation in each location considers roads near the controlled ramp of interest, shown in Figures 11 and 12. The impact to other areas is generally negligible.

For location A, both the ALINEA and LSC methods show the ability to substantially reduce average travel time and VHT for both vehicle classes. ALINEA reduces VHT by 10% and average travel time by 5%, whereas LSC reduces VHT by 15% and average travel time by 9%. VMT would not be reduced as much since travelers are likely to take deviated routes due to ramp metering. Overall, LSC has a better performance in reducing overall congestion since it avoids severe congestion on the ramp and its spill over to local streets. Additionally, both methods effectively reduce fuel use and emissions for cars, ranging from 7% to 10%. However, the change in metrics for trucks is small before and after the implementation of ramp metering control. This can be attributed to the dominance of cars in the traffic flow and their higher sensitivity to the control strategies implemented. LSC outperforms ALINEA in terms of a greater reduction in average travel time, VHT and VMT. However, when it comes to emissions, both ALINEA and LSC exhibit similar performance without significant differences.

For location B, similar results can be found that both the ALINEA and LSC methods are able to reduce average travel time compared to the no control scenario, and LSC outperforms ALINEA in terms of achieving a greater reduction in average travel time and delay for both vehicle classes. ALINEA does not necessarily reduce VHT or VMT, implying its impact to traffic mitigation is minimal in this case. However, LSC is consistently effective in managing traffic, reducing average travel time by 10% and average travel time by 5%. Similar to the results in location A, LSC can effectively reduce fuel use and emissions, ranging from 5% to 9%, outperforming ALINEA.

Table 3 summarizes the average vehicle delay on the ramp and (immediate) downstream highway segment for the two locations. It can be seen that ALINEA causes a larger average delay on the ramp and LSC is able to effectively balance the delay on both controlled ramp and downstream highway, ensuring equity among highways and arterials.

7.3 Results of Scenarios with Various Demand Level and Incident Effect

After identifying LSC as the preferred control strategy, the effectiveness and sensitivity of LSC are tested to various demand levels and the possible occurrence of an incident on I-70. Four scenarios are created for each location: (1) reduced demand (scalar of 0.9), (2) original calibrated demand (scalar of 1.0), (3) increased demand (scalar of 1.1), (4) increased demand (scalar of 1.2), and (5) calibrated demand with an incident. The aggregated metrics are summarized in Tables 4 and 5.

The results show that for both two locations, when demand increases, both traffic and environmental impact metrics remains relatively unchanged, implying LSC is able to accommodate demand within a reasonable range. Even under a major incident on I-70, the average travel time does not change as much for both cars and trucks, ensuring a robust and satisfactory performance of LSC with different levels of demand and incidence occurrence. It is worth noting that the average delay and travel time with the selected areas (Figures 11 and 12) tend to increase slightly because vehicles may deviate to use this selected area as a result of its improved performance. This deviation is more profound when an incident occurs on I-70, especially for location B.

8. Conclusion

This project develops control strategies for ramp metering and local signal synchronization with the establishment of a simulation-based dynamic network model for Maryland's TSMO 1 system. First, a mesoscopic network simulation model is developed with a signal control module for coordinated signalized intersections and ramp metering. Second, multi-source data are collected, and a data-driven calibration framework is adopted to calibrate the dynamic network model. The result demonstrates the calibrated model has a satisfactory accuracy to reproduce the actual traffic conditions. Mesoscopic network simulation is also computationally efficient to performance. One run of all 250,000 vehicles across 15,376 O-D pairs takes less than three minutes on a regular i-5 desktop computer. Furthermore, two control strategies are developed and tested to control metering rates at different ramps along the I-70 corridor with the objective of minimizing system-level congestion ensuring equity among highways and arterials. Finally, several scenarios with different demand levels, control strategies, and incident occurrence are created to examine the effectiveness and robustness of the proposed control methods. Results show that the LSC method outperforms ALINEA in terms of achieving a greater reduction in average travel time, VMT and VHT, and ensuring a good balance of vehicle delay on both ramps and immediate downstream highway segments. It is recommended to Maryland Department of Transportation to consider coordination among ramp metering and localized signal control to achieve the best performance and equity. The mesoscopic network simulation model developed for this project can also be quickly adopted for assessing and optimizing other ITS strategies as well, such as traffic routing, traveler information provision, tolling, HOV lanes, queue warning and incident management.

control policy	vehicle class	trips	VHT (hour)	VMT (miles)	Average travel time (min)	Average travel distance (miles)	fuel (gallon)	CO2 (kg)	HC (kg)	CO (kg)	NOX (kg)
No control	car	32,076	910.07	61,977.15	1.7	1.93	2,341.50	20,808.95	36.18	88.81	72.24
	truck	3,471	129.57	9,117.63	2.24	2.63	536.86	4,771.11	10.61	65.37	61.37
ALINEA	car	30,483	821.01	58,160.07	1.61	1.9	2,197.80	19,532.15	33.58	83.44	67.75
	truck	3,471	126.44	9,164.72	2.19	2.64	540.17	4,800.52	10.57	66	61.6
LSC	car	29,392	764.07	54,964.15	1.55	1.87	2,085.90	18,537.70	31.55	79.22	64.14
	truck	3,404	122.47	8,953.96	2.16	2.63	529.13	4,702.44	10.27	64.9	60.21

Table 1. Metrics for Three Scenarios on Location A

control policy	vehicle class	trips	VHT (hour)	VMT (miles)	Average travel time (min)	Average travel distance (miles)	fuel (gallon)	CO2 (kg)	HC (kg)	CO (kg)	NOX (kg)
No control	car	38,672	1,043.61	70,753.94	1.62	1.83	2,684.78	23,859.66	41.03	101.83	82.63
	truck	3,599	135.69	9,644.81	2.26	2.68	569.15	5,058.02	11.11	69.75	64.88
ALINEA	car	40,050	1,069.88	71,806.56	1.60	1.79	2,701.71	24,010.06	42.05	102.15	83.41
	truck	3,547	129.69	9,001.69	2.19	2.54	528.17	4,693.85	10.56	63.96	60.41
LSC	car	36,631	937.16	65,738.94	1.54	1.79	2,491.11	22,138.49	37.85	94.62	76.71
	truck	3,612	126.18	9,020.51	2.10	2.50	532.19	4,729.53	10.39	65.15	60.64

Table 2. Metrics for Three Scenarios on Location B

location	control method	average delay of ramp (5 sec increments)	average delay of downstream highway (5 sec increments)
A	ALINEA	7.07	5.19
	LSC	5.04	5.31
B	ALINEA	6.11	5.01
	LSC	5.95	5.25

Table 3. Comparison of Average Vehicle Delay on the Ramp and Downstream Highway

scenario	vehicle class	trips	VHT (hour)	VMT (miles)	Average travel time (min)	Average travel distance (miles)	fuel (gallon)	CO2 (kg)	HC (kg)	CO (kg)	NOX (kg)
demand x0.9	car	28,580	796.18	56,291.15	1.67	1.97	2,124.71	18,882.26	32.53	80.74	65.57
	truck	3,269	119.69	8,655.18	2.20	2.65	509.84	4,530.97	10.00	62.21	58.19
demand x1.0	car	29,392	764.07	54,964.15	1.55	1.87	2,085.90	18,537.70	31.55	79.22	64.14
	truck	3,404	122.47	8,953.96	2.16	2.63	529.13	4,702.44	10.27	64.9	60.21
demand x1.1	car	29,473	793.20	56,896.43	1.61	1.93	2,156.96	19,168.94	32.70	81.94	66.38
	truck	3,688	133.39	9,732.51	2.17	2.64	574.97	5,109.73	11.17	70.49	65.45
demand x1.2	car	30,156	797.29	57,265.51	1.59	1.90	2,170.77	19,291.65	32.92	82.46	66.81
	truck	3,888	141.38	10,329.25	2.18	2.66	610.29	5,423.60	11.86	74.83	69.46
demand x1.0 with an incident	car	27,808	849.14	57,657.69	1.83	2.07	2,167.35	19,261.28	33.83	81.87	66.90
	truck	3,486	144.47	9,777.55	2.49	2.80	570.70	5,071.77	11.72	68.16	65.50

Table 4. Metrics for LSC Method on Location A

scenario	vehicle class	trips	VHT (hour)	VMT (miles)	Average travel time (min)	Average travel distance (miles)	fuel (gallon)	CO2 (kg)	HC (kg)	CO (kg)	NOX (kg)
demand x0.9	car	36,734	975.46	67,917.76	1.59	1.85	2,570.94	22,847.92	39.20	97.62	79.21
	truck	3,320	118.40	8,395.00	2.14	2.53	494.55	4,395.07	9.70	60.47	56.44
demand x1.0	car	36,631	937.16	65,738.94	1.54	1.79	2,491.11	22,138.49	37.85	94.62	76.71
	truck	3,612	126.18	9,020.51	2.10	2.50	532.19	4,729.53	10.39	65.15	60.64
demand x1.1	car	42,297	1,225.66	79,381.78	1.74	1.88	2,975.91	26,446.88	46.92	112.58	92.17
	truck	3,800	145.29	9,911.23	2.29	2.61	576.19	5,120.61	11.83	68.68	66.52
demand x1.2	car	43,270	1,290.65	81,165.09	1.79	1.88	3,011.52	26,763.36	48.88	113.14	93.55
	truck	4,006	162.42	10,603.13	2.43	2.65	611.25	5,432.17	13.01	71.66	70.87
demand x1.0 with an incident	car	38,561	1,027.97	70,485.65	1.60	1.83	2,668.95	23,718.95	40.83	101.27	82.22
	truck	3,523	123.91	8,857.39	2.11	2.51	522.96	4,647.53	10.18	64.16	59.57

Table 5. Metrics for LSC Method on Location B

References

- [1] Weiran Yao and Sean Qian. Learning to recommend signal plans under incidents with real-time traffic prediction. *Transportation Research Record*, 2674(6):45–59, 2020.
- [2] Stephen D. Boyles, Nicholas E. Lownes, and A. Unnikrishnan. *Transportation Network Analysis*, volume 1. 0.85 edition, 2020.
- [3] Daiheng Ni. Multiscale modeling of traffic flow. *Mathematica Aeterna*, 1(1):27–54, 2011.
- [4] Wen-Long Jin. Point queue models: A unified approach. *Transportation Research Part B: Methodological*, 77:1–16, 2015.
- [5] Stephen D Boyles and Natalia Ruiz Juri. Queue spillback and demand uncertainty in dynamic network loading. *Transportation Research Record*, 2673(2):38–48, 2019.
- [6] HM Zhang, Yu Nie, and Zhen Qian. Modelling network flow with and without link interactions: the cases of point queue, spatial queue and cell transmission model. *Transportmetrica B: Transport Dynamics*, 1(1):33–51, 2013.
- [7] Carlos F Daganzo. The cell transmission model, part ii: network traffic. *Transportation Research Part B: Methodological*, 29(2):79–93, 1995.
- [8] Michael James Lighthill and Gerald Beresford Whitham. On kinematic waves ii. a theory of traffic flow on long crowded roads. *Proceedings of the Royal Society of London. Series A. Mathematical and Physical Sciences*, 229(1178):317–345, 1955.
- [9] Paul I Richards. Shock waves on the highway. *Operations research*, 4(1):42–51, 1956.
- [10] Wen-Long Jin. A link queue model of network traffic flow. *arXiv preprint arXiv:1209.2361*, 2012.
- [11] Ke Han, Benedetto Piccoli, and WY Szeto. Continuous-time link-based kinematic wave model: formulation, solution existence, and well-posedness. *Transportmetrica B: Transport Dynamics*, 4(3):187–222, 2016.
- [12] Wen-Long Jin. Continuous formulations and analytical properties of the link transmission model. *Transportation Research Part B: Methodological*, 74:88–103, 2015.
- [13] Carolina Osorio, Gunnar Flötteröd, and Michel Bierlaire. Dynamic network loading: A stochastic differentiable model that derives link state distributions. *Transportation Research Part B: Methodological*, 45(9):1410–1423, 2011. Select Papers from the 19th ISTTT.
- [14] Gunnar Flötteröd and C Osorio. Stochastic network link transmission model. *Transportation Research Part B: Methodological*, 102:180–209, 2017.
- [15] Yu Nie. A variational inequality approach for inferring dynamic origin-destination travel demands. University of California, Davis, 2006.
- [16] WL Jin and H Michael Zhang. On the distribution schemes for determining flows through a merge. *Transportation Research Part B: Methodological*, 37(6):521–540, 2003.

- [17] Xidong Pi, Wei Ma, and Zhen Sean Qian. A general formulation for multi-modal dynamic traffic assignment considering multi-class vehicles, public transit and parking. *Transportation Research Part C: Emerging Technologies*, 104:369–389, 2019.
- [18] Nie Yu, Jingtao Ma, and H Michael Zhang. A polymorphic dynamic network loading model. *Computer- Aided Civil and Infrastructure Engineering*, 23(2):86–103, 2008.
- [19] Wei Ma, Xidong Pi, and Zhen Qian. Estimating multi-class dynamic origin-destination demand through a forward-backward algorithm on computational graphs. *Transportation Research Part C: Emerging Technologies*, 102747, 2020. arXiv: 1903.04681.
- [20] Jingtao Ma. An efficiency-equity solution to the integrated transportation corridor control design problem. Ph.D. Dissertation, University of California, Davis, 2008.
- [21] Richard Mounce. Existence of equilibrium in a continuous dynamic queueing model for traffic networks. In 4th IMA International Conference on Mathematics in Transport Institute of Mathematics and its Applications, 2007.
- [22] Terry L Friesz, David Bernstein, Tony E Smith, Roger L Tobin, and Byung-Wook Wie. A variational inequality formulation of the dynamic network user equilibrium problem. *Operations research*, 41(1):179–191, 1993.
- [23] Pinchao Zhang and Sean Qian. Path-based system optimal dynamic traffic assignment: A subgradient approach. *Transportation Research Part B: Methodological*, 134:41–63, 2020.
- [24] Zhen Sean Qian, Wei Shen, and H. M. Zhang. System-optimal dynamic traffic assignment with and without queue spillback: Its path-based formulation and solution via approximate path marginal cost. *Transportation Research Part B: Methodological*, 46(7):874–893, 2012.
- [25] Zhen Sean Qian and H Michael Zhang. A hybrid route choice model for dynamic traffic assignment. *Networks and Spatial Economics*, 13(2):183–203, 2013.
- [26] Wei Ma and Zhen Sean Qian. Estimating multi-year 24/7 origin-destination demand using high-granular multi-source traffic data. *Transportation Research Part C: Emerging Technologies*, 96:96–121, 2018.
- [27] Zhong Zhou, Anthony Chen, and Shlomo Bekhor. C-logit stochastic user equilibrium model: formulations and solution algorithm. *Transportmetrica*, 8(1):17–41, 2012.
- [28] Joseph N Prashker and Shlomo Bekhor. Route choice models used in the stochastic user equilibrium problem: a review. *Transport reviews*, 24(4):437–463, 2004.
- [29] Shanjiang Zhu, David Levinson, Henry X Liu, and Kathleen Harder. The traffic and behavioral effects of the i-35w mississippi river bridge collapse. *Transportation research part A: policy and practice*, 44(10):771–784, 2010.
- [30] Adam Danczyk, Xuan Di, Henry X Liu, and David M Levinson. Unexpected versus expected network disruption: Effects on travel behavior. *Transport Policy*, 57:68–78, 2017.
- [31] Xiaozheng He and Henry X Liu. Modeling the day-to-day traffic evolution process after an unexpected network disruption. *Transportation Research Part B: Methodological*, 46(1):50–71, 2012.

- [32] Michael Zhang and Sean Qian. Integrated work zone traffic management. Technical report, 2011.
- [33] Hirsh Majid, Chao Lu, and Hardy Karim. An integrated approach for dynamic traffic routing and ramp metering using sliding mode control. *Journal of Traffic and Transportation Engineering (English Edition)*, 5(2):116–128, 2018.
- [34] Rasool Mohebifard and Ali Hajbabaie. Distributed optimization and coordination algorithms for dynamic traffic metering in urban street networks. *IEEE Transactions on Intelligent Transportation Systems*, 20(5):1930–1941, 2018.
- [35] Ioannis Papamichail, Apostolos Kotsialos, Ioannis Margonis, and Markos Papageorgiou. Coordinated ramp metering for freeway networks—a model-predictive hierarchical control approach. *Transportation Research Part C: Emerging Technologies*, 18(3):311–331, 2010.
- [36] H Michael Zhang, Jingtao Ma, and Yu Nie. Local synchronization control scheme for congested interchange areas in freeway corridor. *Transportation research record*, 2128(1):173–183, 2009.
- [37] RL Landman, A Hegyi, and SP Hoogendoorn. Coordinated ramp metering based on on-ramp saturation time synchronization. *Transportation Research Record*, 2484(1):50–59, 2015.
- [38] Ajith Muralidharan, Gunes Dervisoglu, and Roberto Horowitz. Freeway traffic flow simulation using the link node cell transmission model. In *2009 American Control Conference*, pages 2916–2921. IEEE, 2009.
- [39] Rodrigo C Carlson, Ioannis Papamichail, Markos Papageorgiou, and Albert Messmer. Optimal motorway traffic flow control involving variable speed limits and ramp metering. *Transportation science*, 44(2):238–253, 2010.
- [40] Joseph A Wattleworth. Peak-period analysis and control of a freeway system. Technical report, Texas Transportation Institute, 1965.
- [41] Markos Papageorgiou, Habib Hadj-Salem, Jean-Marc Blosseville, et al. Alinea: A local feedback control law for on-ramp metering. *Transportation research record*, 1320(1):58–67, 1991.
- [42] Mohammed A Hadi. Coordinated traffic responsive ramp metering strategies-an assessment based on previous studies. In *12th World Congress on Intelligent Transport SystemsITS AmericaITS JapanER- TICO*, 2005.
- [43] Minha Lee, Zheng Zhu, Chenfeng Xiong, and Lei Zhang. Dynamic traffic assignment integration with real-time ramp metering for large-scale network management. In *2017 5th IEEE International Conference on Models and Technologies for Intelligent Transportation Systems (MT-ITS)*, pages 463–468. IEEE, 2017.
- [44] Seiran Heshami and Lina Kattan. Ramp metering control under stochastic capacity in a connected environment: A dynamic bargaining game theory approach. *Transportation Research Part C: Emerging Technologies*, 130:103282, 2021.

- [45] Tarikul Islam, Hai L Vu, Manoj Panda, and Dong Ngoduy. A study of realistic dynamic traffic assignment with signal control, time-scale, and emission. *Journal of Intelligent Transportation Systems*, 22(5):446–461, 2018.
- [46] Tarikul Islam, Hai L Vu, Manoj Panda, Nam Hoang, and Dong Ngoduy. The accuracy of cell-based dynamic traffic assignment: Impact of signal control on system optimality. *arXiv preprint arXiv:1708.03759*, 2017.
- [47] Khaled F Abdelghany, Didier M Valdes, Akmal S Abdelfatah, and Hani S Mahmassani. Real-time dynamic traffic assignment and path-based signal coordination; application to network traffic management. *Transportation research record*, 1667(1):67–76, 1999.
- [48] Akmal S Abdelfatah and Hani S Mahmassani. A simulation-based signal optimization algorithm within a dynamic traffic assignment framework. In *ITSC 2001. 2001 IEEE Intelligent Transportation Systems. Proceedings (Cat. No. 01TH8585)*, pages 428–433. IEEE, 2001.
- [49] Huajun Chai, H Michael Zhang, Dipak Ghosal, and Chen-Nee Chuah. Dynamic traffic routing in a network with adaptive signal control. *Transportation Research Part C: Emerging Technologies*, 85:64–85, 2017.
- [50] Ali Hajbabaie and Rahim F Benekohal. Does traffic metering improve network performance efficiency? In *2011 14th International IEEE Conference on Intelligent Transportation Systems (ITSC)*, pages 1114–1119. IEEE, 2011.
- [51] Milan Zlatkovic and Xuesong Zhou. Integration of signal timing estimation model and dynamic traffic assignment in feedback loops: system design and case study. *Journal of Advanced Transportation*, 49(6):683–699, 2015.
- [52] Ke Han, Vikash V Gayah, Benedetto Piccoli, Terry L Friesz, and Tao Yao. On the continuum approximation of the on-and-off signal control on dynamic traffic networks. *Transportation Research Part B: Methodological*, 61:73–97, 2014.
- [53] Ke Han and Vikash V Gayah. Continuum signalized junction model for dynamic traffic networks: Offset, spillback, and multiple signal phases. *Transportation Research Part B: Methodological*, 77:213–239, 2015.
- [54] Tobias Pohlmann and Bernhard Friedrich. Online control of signalized networks using the cell transmission model. In *13th International IEEE Conference on Intelligent Transportation Systems*, pages 1–6. IEEE, 2010.
- [55] Lee K Jones, Rahul Deshpande, Nathan H Gartner, Chronis Stamatiadis, and Fei Zou. Robust controls for traffic networks: The near-bayes near-minimax strategy. *Transportation Research Part C: Emerging Technologies*, 27:205–218, 2013.
- [56] Hualing Ren, Haoxiang Liu, Jiancheng Long, and Ziyu Gao. Dynamic user optimal signal design at isolated intersections. *PROMET-Traffic&Transportation*, 25(1):13–22, 2013.
- [57] Ludovica Adacher and Andrea Gemma. A robust algorithm to solve the signal setting problem considering different traffic assignment approaches. *International Journal of Applied Mathematics and Computer Science*, 27(4), 2017.

- [58] L Adacher. A global optimization approach to solve the traffic signal synchronization problem. *Procedia-Social and Behavioral Sciences*, 54:1270–1277, 2012.
- [59] Mehrzad Mehrabipour, Leila Hajibabai, and Ali Hajbabaie. A decomposition scheme for parallelization of system optimal dynamic traffic assignment on urban networks with multiple origins and destinations. *Computer-Aided Civil and Infrastructure Engineering*, 34(10):915–931, 2019.
- [60] Markos Papageorgiou and Apostolos Kotsialos. Freeway ramp metering: An overview. *IEEE transactions on intelligent transportation systems*, 3(4):271–281, 2002.
- [61] Dipl-Ing Svetlana Vukanovic and Dipl-Ing Oliver Ernhof. Field evaluation of the fuzzy logic based ramp metering algorithm. *IFAC Proceedings Volumes*, 39(12):119–123, 2006.
- [62] Juntao Gao, Yulong Shen, Jia Liu, Minoru Ito, and Norio Shiratori. Adaptive traffic signal control: Deep reinforcement learning algorithm with experience replay and target network. *arXiv preprint arXiv:1705.02755*, 2017.
- [63] Richard S Sutton and Andrew G Barto. *Reinforcement learning: An introduction*. MIT press, 2018.
- [64] D Tabac. A linear programming model of highway traffic control. In *Proc. 6th Annu. Princeton Conf. Information Science and Systems*, pages 568–570, 1972.
- [65] Cheng-I Chen, Jos’e B Cruz Jr, and Jean G Paquet. Entrance ramp control for travel-rate maximization in expressways. *Transportation Research*, 8(6):503–508, 1974.
- [66] Emmanouil Smaragdis and Markos Papageorgiou. Series of new local ramp metering strategies: Emmanouil smaragdis and markos papageorgiou. *Transportation Research Record*, 1856(1):74–86, 2003.
- [67] H Michael Zhang and Stephen G Ritchie. Freeway ramp metering using artificial neural networks. *Transportation Research Part C: Emerging Technologies*, 5(5):273–286, 1997.
- [68] Tom Bellemans, Bart De Schutter, and Bart De Moor. Model predictive control with repeated model fitting for ramp metering. In *Proceedings. The IEEE 5th International Conference on Intelligent Transportation Systems*, pages 236–241. IEEE, 2002.
- [69] Apostolos Kotsialos, Markos Papageorgiou, and Frans Middelham. Local and optimal coordinated ramp metering for freeway networks. *Journal of Intelligent Transportation Systems*, 9(4):187–203, 2005.

- [70] Rasool Mohebifard and Ali Hajbabaie. Dynamic traffic metering in urban street networks: Formulation and solution algorithm. *Transportation research part C: emerging technologies*, 93:161–178, 2018.
- [71] Francois Belletti, Daniel Haziza, Gabriel Gomes, and Alexandre M Bayen. Expert level control of ramp metering based on multi-task deep reinforcement learning. *IEEE Transactions on Intelligent Transportation Systems*, 19(4):1198–1207, 2017.
- [72] Chao Lu, Jie Huang, Lianbo Deng, and Jianwei Gong. Coordinated ramp metering with equity consideration using reinforcement learning. *Journal of Transportation Engineering, Part A: Systems*, 143(7):04017028, 2017.
- [73] Yue Zhou, Kaan Ozbay, Pushkin Kachroo, and Fan Zuo. Ramp metering for a distant downstream bottleneck using reinforcement learning with value function approximation. *Journal of Advanced Transportation*, 2020, 2020.
- [74] Venkatesh Pandey, Evana Wang, and Stephen D Boyles. Deep reinforcement learning algorithm for dynamic pricing of express lanes with multiple access locations. *Transportation Research Part C: Emerging Technologies*, 119:102715, 2020.
- [75] Timothy P Lillicrap, Jonathan J Hunt, Alexander Pritzel, Nicolas Heess, Tom Erez, Yuval Tassa, David Silver, and Daan Wierstra. Continuous control with deep reinforcement learning. *arXiv preprint arXiv:1509.02971*, 2015.
- [76] Tuomas Haarnoja, Aurick Zhou, Kristian Hartikainen, George Tucker, Sehoon Ha, Jie Tan, Vikash Kumar, Henry Zhu, Abhishek Gupta, Pieter Abbeel, et al. Soft actor-critic algorithms and applications. *arXiv preprint arXiv:1812.05905*, 2018.
- [77] Posted by By wxinix and wxinix View All Posts, Mar 2021.
- [78] Javier García and Fernando Fernández. A comprehensive survey on safe reinforcement learning. *Journal of Machine Learning Research*, 16(1):1437–1480, 2015.
- [79] Peter Koonce and Lee Rodegerdts. Traffic signal timing manual. Technical report, United States. Federal Highway Administration, 2008.
- [80] William R McShane and Roger P Roess. *Traffic engineering*. 1990.
- [81] John DC Little, Mark D Kelson, and Nathan H Gartner. Maxband: A versatile program for setting signals on arteries and triangular networks. 1981.
- [82] Seung-Bae Cools, Carlos Gershenson, and Bart D’Hooghe. Self-organizing traffic lights: A realistic simulation. In *Advances in applied self-organizing systems*, pages 45–55. Springer, 2013.
- [83] Pravin Varaiya. The max-pressure controller for arbitrary networks of signalized intersections. In *Advances in Dynamic Network Modeling in Complex Transportation Systems*, pages 27–66. Springer, 2013.

- [84] Aleksandar Stevanovic and Peter T Martin. Split-cycle offset optimization technique and coordinated actuated traffic control evaluated through microsimulation. *Transportation Research Record*, 2080(1):48–56, 2008.
- [85] Hua Wei, Guanjie Zheng, Vikash Gayah, and Zhenhui Li. A survey on traffic signal control methods. *arXiv preprint arXiv:1904.08117*, 2019.
- [86] HM Abdul Aziz and Satish V Ukkusuri. Unified framework for dynamic traffic assignment and signal control with cell transmission model. *Transportation Research Record*, 2311(1):73–84, 2012.
- [87] Christopher Beard and Athanasios Ziliaskopoulos. System optimal signal optimization formulation. *Transportation research record*, 1978(1):102–112, 2006.
- [88] Ping Wang, LS Jones, Qun Yang, and S Gurupackiam. Cell transmission model based traffic signal timing in oversaturated conditions. *Journal of Central South University*, 20(4):1129–1136, 2013.
- [89] Zichuan Li. Modeling arterial signal optimization with enhanced cell transmission formulations. *Journal of Transportation Engineering*, 137(7):445–454, 2011.
- [90] Ryan Lowe, Yi Wu, Aviv Tamar, Jean Harb, Pieter Abbeel, and Igor Mordatch. Multi-agent actor-critic for mixed cooperative-competitive environments. *arXiv preprint arXiv:1706.02275*, 2017.
- [91] Tabish Rashid, Mikayel Samvelyan, Christian Schroeder, Gregory Farquhar, Jakob Foerster, and Shimon Whiteson. Qmix: Monotonic value function factorisation for deep multi-agent reinforcement learning. In *International Conference on Machine Learning*, pages 4295–4304. PMLR, 2018.
- [92] Huichu Zhang, Siyuan Feng, Chang Liu, Yaoyao Ding, Yichen Zhu, Zihan Zhou, Weinan Zhang, Yong Yu, Haiming Jin, and Zhenhui Li. Cityflow: A multi-agent reinforcement learning environment for large scale city traffic scenario. In *The World Wide Web Conference*, pages 3620–3624, 2019.
- [93] Tianshu Chu, Jie Wang, Lara Codecà, and Zhaojian Li. Multi-agent deep reinforcement learning for large-scale traffic signal control. *IEEE Transactions on Intelligent Transportation Systems*, 21(3):1086–1095, 2019.
- [94] Chacha Chen, Hua Wei, Nan Xu, Guanjie Zheng, Ming Yang, Yuanhao Xiong, Kai Xu, and Zhenhui Li. Toward a thousand lights: Decentralized deep reinforcement learning for large-scale traffic signal control. In *Proceedings of the AAAI Conference on Artificial Intelligence*, volume 34, pages 3414–3421, 2020.
- [95] Markos Papageorgiou. An integrated control approach for traffic corridors. *Transportation Research Part C: Emerging Technologies*, 3(1):19–30, 1995.
- [96] Dongyan Su, Xiao-Yun Lu, Roberto Horowitz, and Zhongren Wang. Coordinated ramp metering and intersection signal control. *International Journal of Transportation Science and Technology*, 3(2):179–192, 2014.

- [97] Xiao-Yun Lu, Dongyan Su, John Spring, Partners for Advanced Transit, and Highways (Calif.). Coordination of Freeway Ramp Meters and Arterial Traffic Signals Field Operational Test (FOT). California PATH Program, Institute of Transportation Studies, University of . . . , 2013.
- [98] Transportation Systems Management and Operations (TSMO) - MDOT SHA
- [99] Leading Transportation Analytics Solutions | INRIX.
- [100] WRA | People Focused - Project Driven.
- [101] US Census Bureau. TIGER/Line Shapefiles. Section: Government.
- [102] Google Maps.
- [103] Sean Qian. Dynamic Network Analysis & Real-time Traffic Management for Philadelphia Metropolitan Area. Final Report WO-004, Carnegie Mellon University, Pittsburgh, PA, September 2016.
- [104] Login | Regional Integrated Transportation Information System. www.ritis.org
- [105] Driving directions, live traffic & road conditions updates.
- [106] Sean Qian, Jia Li, Xiaopeng Li, Michael Zhang, and Haizhong Wang. Modeling heterogeneous traffic flow: A pragmatic approach. Transportation Research Part B: Methodological, 99:183–204, May 2017.
- [107] Habib Haj-Salem and Marcos Papageorgiou. Ramp metering impact on urban corridor traffic: Field results. Transportation Research Part A: Policy and Practice, 29(4):303–319, 1995.
- [108] Michael Zhang, Taewan Kim, Xiaojian Nie, Wenlong Jin, Lianyu Chu, and Will Recker. Evaluation of on-ramp control algorithms. 2001.
- [109] Masroor Hasan, Mithilesh Jha, and Moshe Ben-Akiva. Evaluation of ramp control algorithms using microscopic traffic simulation. Transportation Research Part C: Emerging Technologies, 10(3):229–256, 2002.