Design and Demonstration of an Arterial-friendly Local Ramp Metering Control System

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FINAL RESEARCH REPORT

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All data generated from this project can be accessed from https://github.com/maccmu/macposts

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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 (TSMO) 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 remain 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

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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, we load the vehicles through the network according to the evolution rules defined by link and node models, and we keep moving vehicles until all vehicles reach their destinations. The core components of network flow models or dynamic traffic assignment (DTA) are thus link and 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 models or PQ [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 model or SQ [6] adds 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 or CTM [7] is an explicit solution to 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 or 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 or 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 the 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 PID [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, 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 application is often questioned, since we lack 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 problem 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 its 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 system which adjusts 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, just to name a few, 24/7 traffic counts, traffic speeds, weather conditions, vehicle classifications, incidents, and Waze, 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. A best way is to design control strategies in a predictive manner. Traffic can be predicted for each roadway segment 30-min in advance. Thus, engaging optimal control are designed to prevent substantial queuing proactively.

In view of these research gaps, we propose 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, 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-min 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.

[1] https://github.com/maccmu/macposts

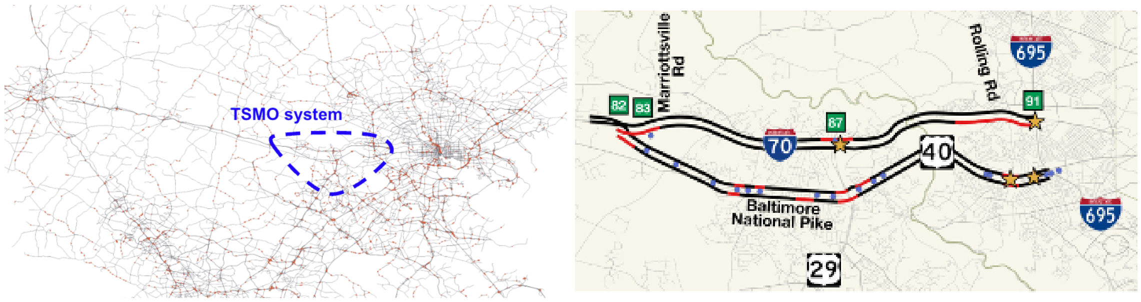


Figure 1: Location of TSMO 1 system

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.

4 Data collection and processing

TSMO is the Maryland Department of Transportation (MDOT) 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.

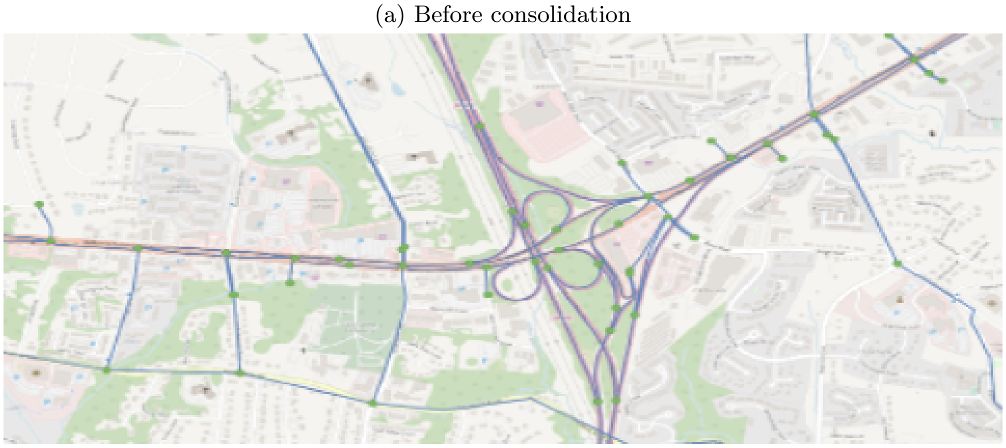
4.1 Network description

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 WRA [100] as well as 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 our model, we collected 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.

4.3 Traffic speed data

Traffic speed data is provided by INRIX and obtained from 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 the speed data is measured every 5 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, we also obtained existing signal time plan for ramps and local intersections of interest from MDOT SHA, which can be integrated into the dynamic network model. Meanwhile, the incident data was acquired from WAZE [105], archived by MDOT SHA, which includes accidents, road closures, or hazardous weather conditions within this area. The incident data is used to

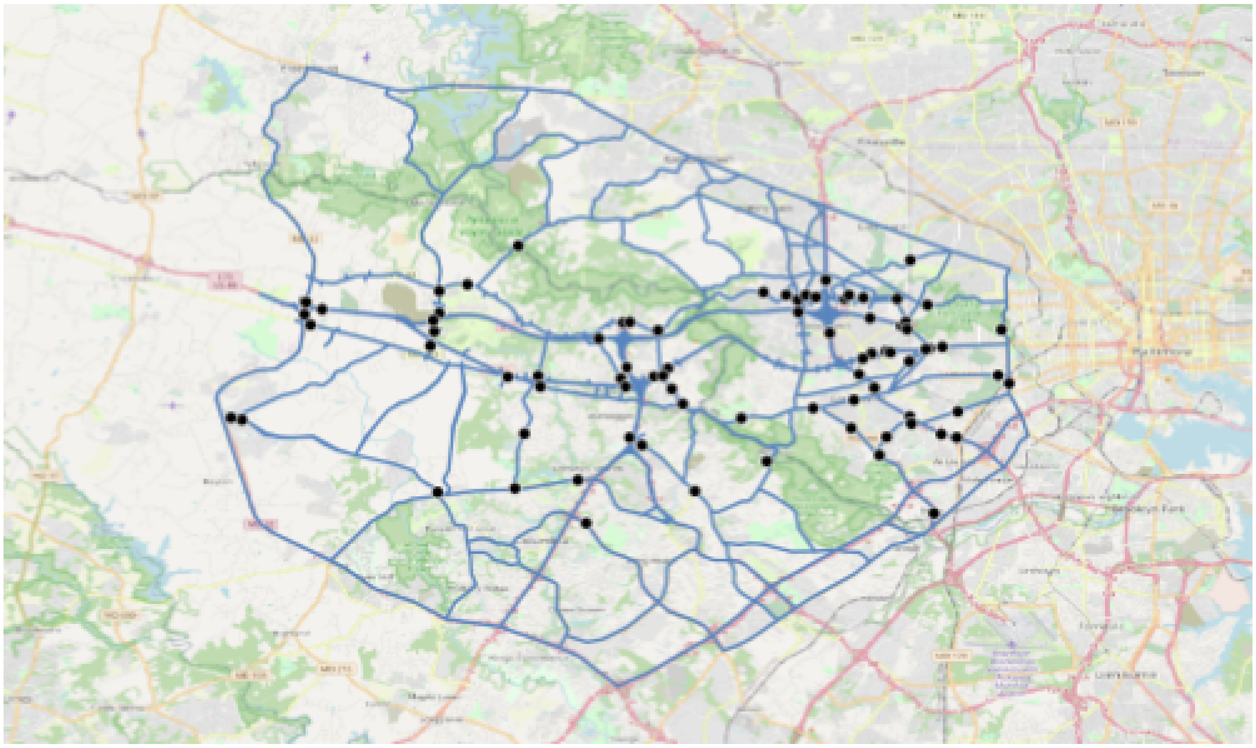


Figure 4: An overview of the traffic count locations

Figure 5: An overview of the speed data (links with observed speed data are marked in red)

distinguish non-recurrent traffic data from recurrent one and thus identify the typical non-recurrent traffic flow patterns.

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 $A_{\to j}$, and the set of all downstream links by $A_{j\to}$. Also, denote the turning proportion from any upstream link $a \in A_{\to j}$ to any downstream link $b \in A_{j\to}$ at time t by $\psi_{a\to b}(t)$, where $\sum_{b\in A_{j\to}} \psi_{a\to b}(t) = 1, \forall a \in A_{\to j}$. The flux from any upstream link $a \in A_{\to j}$ to downstream link $b \in A_{j\to}$:

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

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.

Note that our 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

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

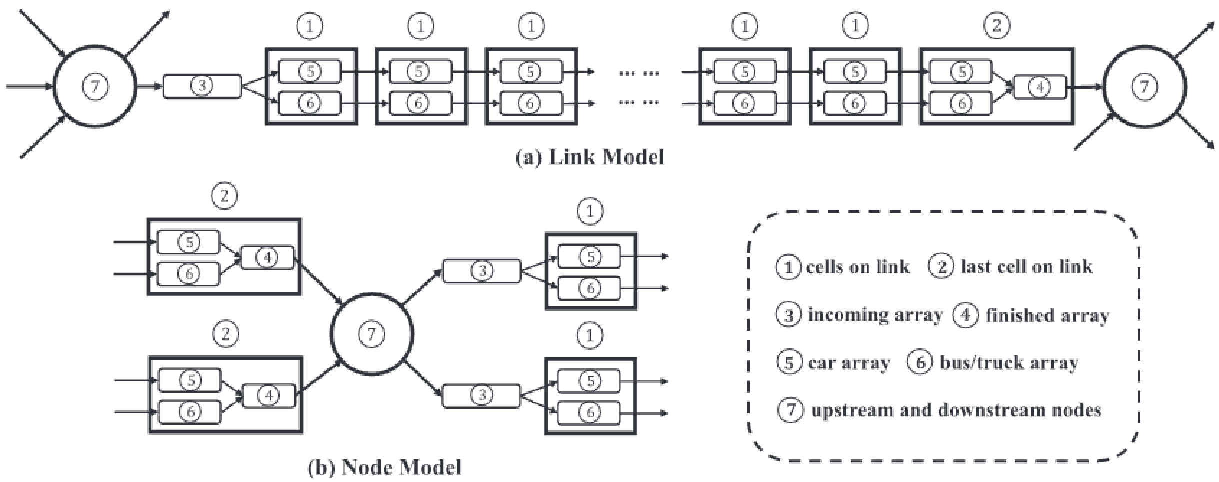


Figure 6: Implementation of link and node models

where q is thel 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.

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

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 occur where the traffic stream on a single link splits 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:

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

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:

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

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

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 can 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; $N^m_{s+1}(t)$ is the storage capacity for vehicles under movement m.

Signalized merges

The flow updating rule for the signalized merge is

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

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:

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

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 :

$$D^t_R = \min(D^t_R, R^t, q_{max}) \tag{9}$$

$$D^t = D^t_M + D^t_R \tag{10}$$

$$S^t = \min(S^t_M, D^t) \tag{11}$$

$$f^t_M = \frac{D^t_M}{D^t} S^t \tag{12}$$

$$f^t_R = \frac{D^t_R}{D^t} S^t \tag{13}$$

where R_t is the ramp metering rate; D^t_R is the ramp demand at time t; D^t is the demand upon the beginning cell of the link downstream of the ramp; D^t_M demand on mainline competing with the ramp demand; S^t_M supply of the beginning cell of the downstream link; S^t is the total service flow rate; f^t_R is the outflow from ramp; and f^t_M 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 DODE problem, which typically deals with single-class vehicle demand, our 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:

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

where $\mathbf{q}_{\text{car}}$ and $\mathbf{q}_{\text{truck}}$ are the car and truck demands, respectively; $\mathbf{y}'_{\text{car}}$ and $\mathbf{y}_{\text{car}}$ are the observed and estimated car flows, respectively; $\mathbf{y}'_{\text{truck}}$ and $\mathbf{y}_{\text{truck}}$ are the observed and estimated truck flows, respectively; $\mathbf{z}'_{\text{car}}$ and $\mathbf{z}_{\text{car}}$ are the observed and estimated car travel times, respectively; $\mathbf{z}'_{\text{truck}}$ and $\mathbf{z}_{\text{truck}}$ 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, we assume 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-min traffic volumes and observed 5-min traffic volumes, in which the vertical axis is the simulated counts and the horizontal axis is the observed counts. 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 a 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 generate 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.

Overall, our 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.

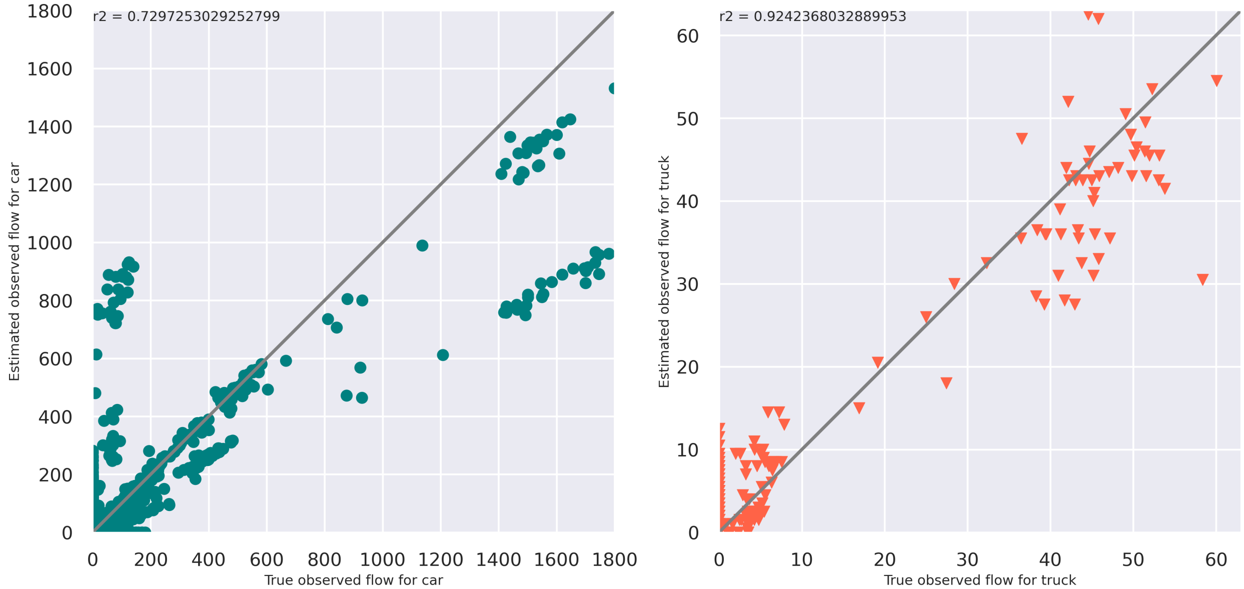


Figure 7: Traffic count calibration (left: car count, right: truck count)

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:

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

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 Fig. 8. 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.

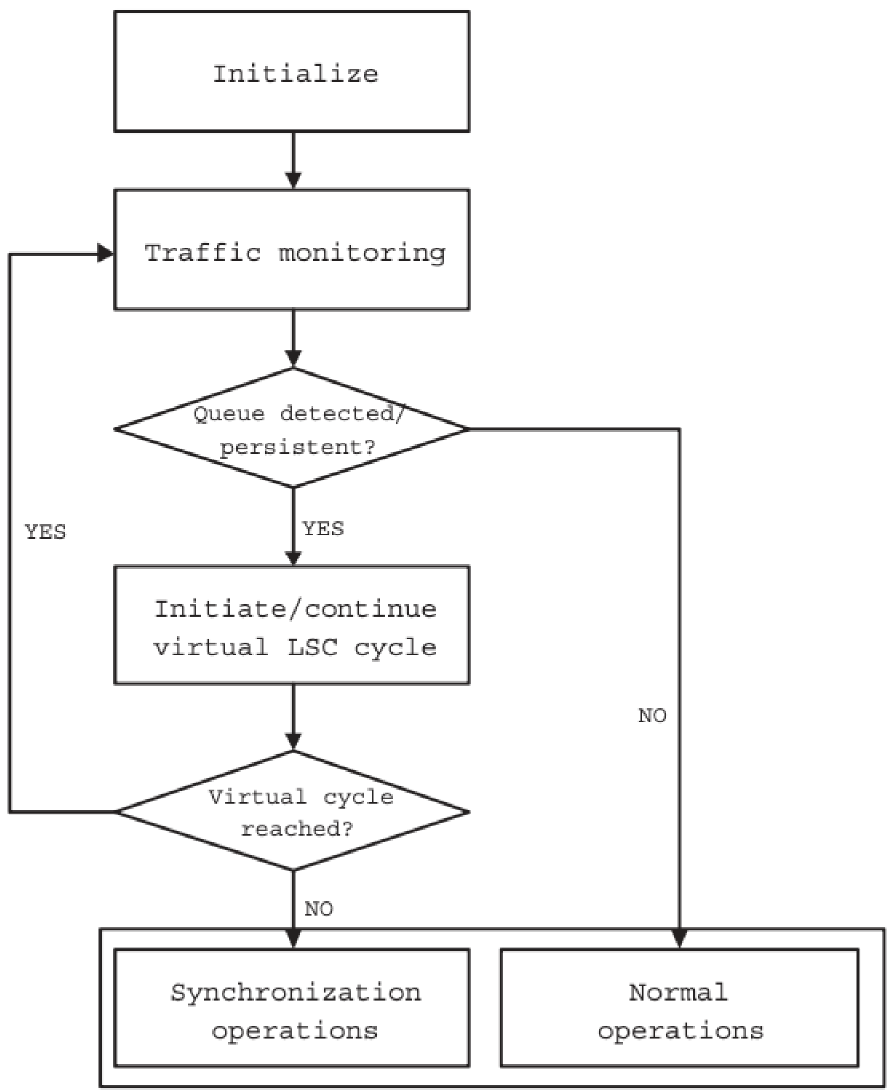


Figure 8: Flowchart of local synchronization control scheme [20].

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 Fig. 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 regards 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 allieve 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 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

The 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.

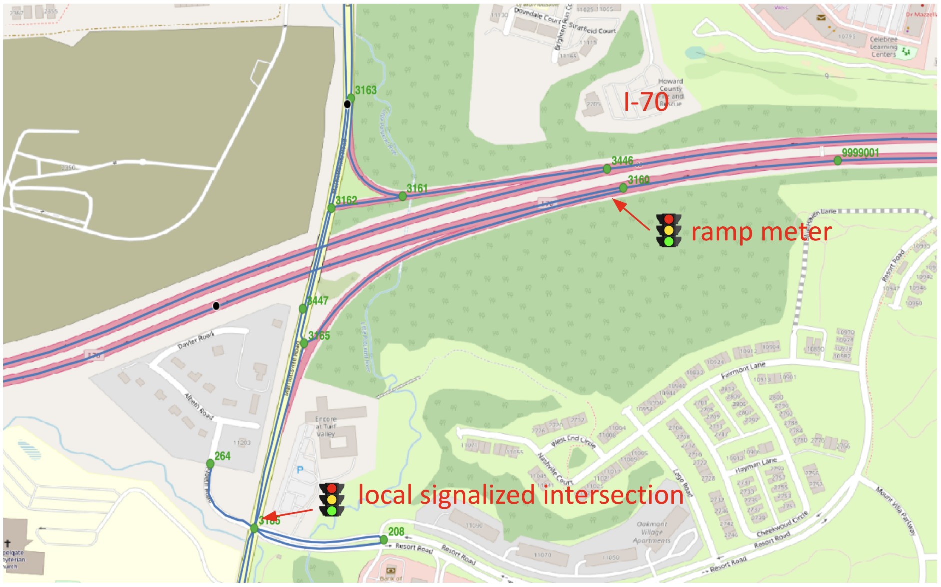


Figure 9: Illustration of the location A on I-70 highway

The 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.

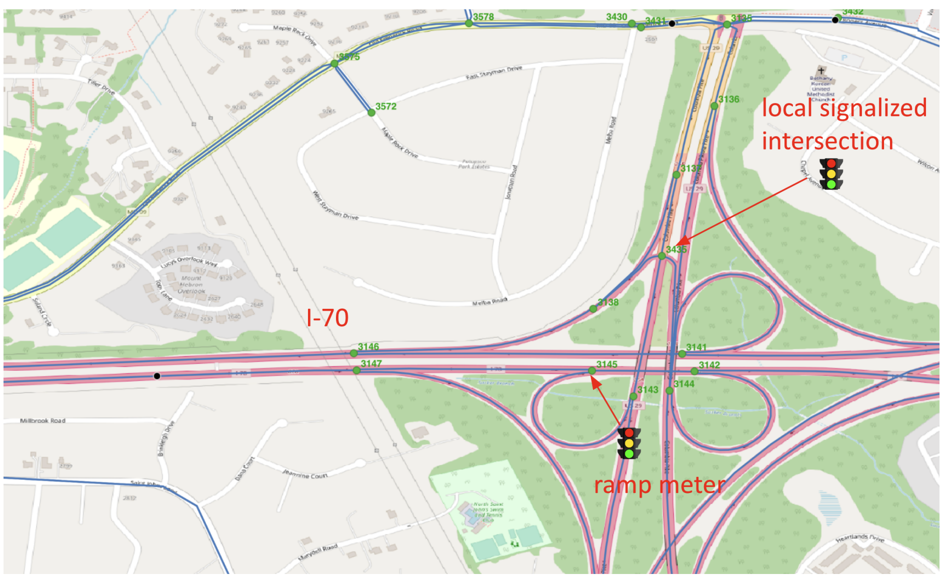


Figure 10: Illustration of location B on I-70 highway

For each location, we set up three scenarios 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 our 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 to analyze the traffic impacts, including vehicle hours traveled (VHT), also known as total travel time, vehicle miles traveled (VMT), average travel time, average travel distance, average vehicle delay which is the average waiting time at intersections for two vehicle classes, and environmental impacts such as fuel use, CO2, NOX, etc. Selected roads used for measure system performance for each control location are highlighted in yellow in Figures 11 and 12.

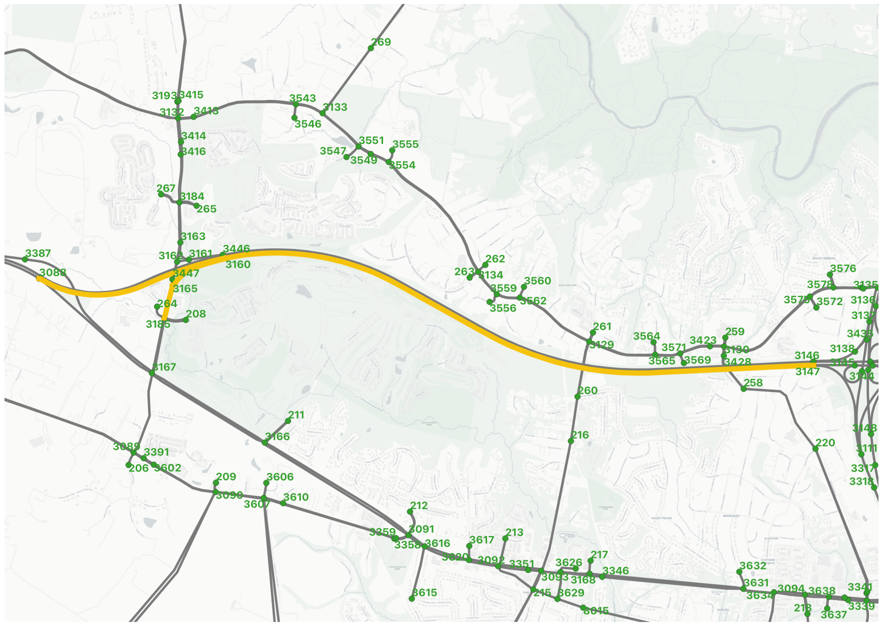


Figure 11: Selected links for location A

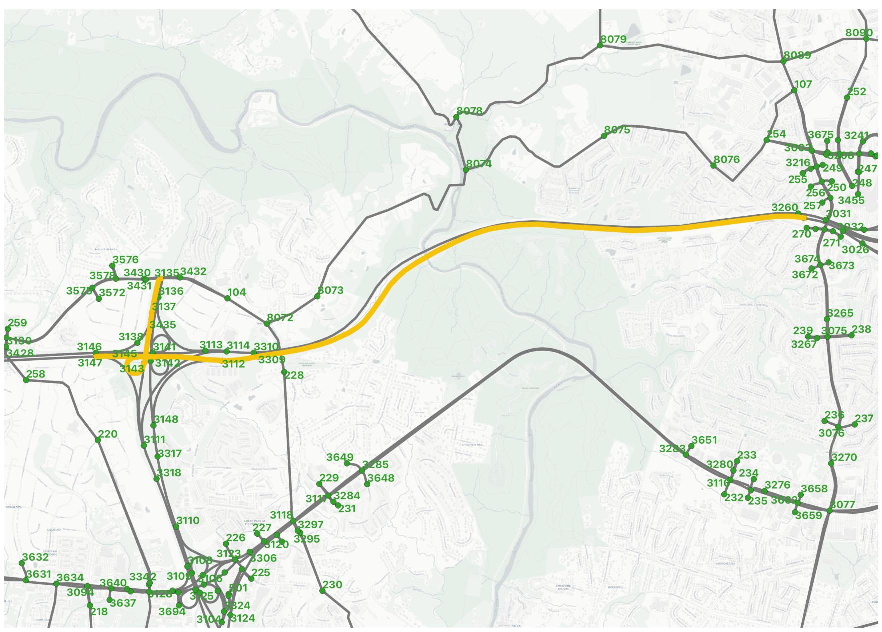


Figure 12: Selected links for location B

For the control strategy with the best performance, we set up five 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

Table 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 the 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 the location A, LSC can effectively reduce fuel use and emissions, raging 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, we test the effectiveness and sensitivity of LSC 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 Table 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 a 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 sytem. First, a mescoscopic 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. Mescoscopic network simulation is also computationally efficient to performance. One run of all 250,000 vehicles across 15,376 O-D pairs takes less than 3 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. Last but not least, 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

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