An Occupancy Based Max-Pressure Algorithm to Provide Transit Signal Priority

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ABSTRACT

Max-pressure (MP) is a decentralized adaptive traffic signal control algorithm that has been shown to maximize throughput for private vehicles; however, MP algorithms do not consider the movement of transit vehicles. Transit signal priority (TSP), on the other hand, aims to grant priority to transit vehicles at traffic signals, improving the reliability and efficiency of transit operations. To balance the trade-off between performance of private vehicles and transit vehicles, this study proposes a novel occupancy-based MP (OCC-MP) algorithm that prioritizes the movement of higher occupancy vehicles (HOV), including buses. OCC-MP specifically considers the average occupancies of upstream queued vehicles and prioritizes the movements with more queued passengers. Doing so implicitly provides priority to transit vehicles without imposing rules or constraints, which makes it applicable to networks with mixed traffic and transit vehicles in shared lanes. Simulations on a grid network under varying demands and transit configurations demonstrate the effectiveness of OCC-MP at providing TSP which simultaneously reducing the negative impact imparted onto lower occupancy vehicles, such as private automobiles. Moreover, the performance of OCC-MP is robust to errors in passenger occupancy information from transit vehicles and can be applied when passenger occupancies of private vehicles are not available. In a fully connected vehicle environment, OCC-MP reduces travel time for higher occupancy passenger vehicles and also outperformed baseline control methods in a partially connected environment. Furthermore, OCC-MP demonstrates a larger stable region within feasible set of demands compared to rule-based TSP strategies integrated into the MP framework.

INTRODUCTION

Adaptive Traffic Signal Control (ATSC) is an intelligent transportation system technology that aims to optimize traffic flow by dynamically adjusting signal timings based on real-time traffic patterns. Max Pressure (MP) is a decentralized ATSC approach that has gained popularity due to its effectiveness in improving vehicle throughput at intersections. Initially developed for packet transmission scheduling in wireless networks (*1*), the MP concept was later extended to traffic signal control by (*2*). MP-based traffic signal control algorithms operate independently at each intersection and rely on local information from approach links upstream and downstream of the intersection. Unlike some other ATSC approaches, MP algorithms do not require knowledge of future traffic demands, making them more practical and applicable in real-world settings. MP control is based on distributing vehicles from longer queues to shorter queues (*3*). Specifically, the control policy assigns the right of way to the phase in a traffic signal that serves movements with higher upstream metrics such as queue length, travel time or delay toward downstream links that are uncongested in order to maximize throughput (*2*, *4–11*). While there have been several variations of the MP algorithm proposed since 2013, most of the research has focused on maximizing throughput for private vehicles without considering its impact on other vehicle classes, especially transit vehicles.

Transit signal priority (TSP) is a traffic engineering technique that aims to enhance the performance of public transportation by granting priority to transit vehicles at traffic signals. Its primary objective is to alleviate delays caused by traffic signals, thereby improving the reliability, efficiency, and speed of public transportation services. TSP techniques can generally be classified into two categories: "active" and "passive." Passive TSP relies on pre-programmed signal timing plans to prioritize public transit vehicles at specific times or on designated routes, without direct communication between the transit vehicle and traffic signals. It is effective for fixed-route bus lines with predictable schedules (*12*, *13*). In contrast, active TSP involves real-time communication between transit vehicles and traffic signals, allowing for dynamic adjustments to signal timing based on the vehicle's needs. Active TSP requires a two-way communication system, with transit vehicles sending requests to the traffic signal system, which then responds by adjusting signal timing through methods like green extension and red truncation (*14–19*). Most of these studies have focused on developing TSP strategies based on fixed cycle lengths or are limited to dedicated bus lanes. As a result, these strategies overlook the potential consequences on private vehicles i.e., overall traffic flow. In addition, these studies rely on rule-based approaches and optimization under various constraints to balance travel time of transit and private vehicles (*20*).

There exists a trade-off between TSP and ATSC in the context of intersection management (*21*). TSP focuses on minimizing delays specifically for transit vehicles at intersections, while ATSC aims to minimize overall vehicle delays without distinguishing between private vehicles and transit. Adaptive-TSP systems are considered to be the most intelligent and effective strategy as they dynamically respond to changing traffic conditions and adjust signal timings accordingly. These systems utilize real-time traffic information to optimize performance measures, such as minimizing delay for both vehicles and passengers. In many cases, the optimization objectives consider prioritizing factors like maximizing person capacity or minimizing person delay, schedule delay, vehicle queues and emissions rather than vehicle-based measures alone (*22–34*). The computational complexity of these problems calls for formulation as mixed integer linear problems that are commonly solved using techniques such as dynamic programming (*35*, *36*), genetic algorithms (*37*, *38*), reinforced learning (*39–42*). With the emergence of connected vehicle (CV) technology, researchers have leveraged two-way communication, precise vehicle location tracking, and passenger count information in TSP research (*37*, *43–46*).

A recent study (*47*) proposed the integration of rule-based TSP into MP control and demonstrated that the policy can outperform fixed-time-TSP and adaptive-TSP policies in reducing vehicle travel times while having the ability to serve a larger demand. However, the proposed policy relies on constraints that reduce the stable region compared to the original max pressure policy. Moreover, the control uses a set of rules that switch between the original control policy and TSP depending on the detection of buses. The application was also limited to arterials with dedicated bus lanes, which limits the applicability of the control policy as most urban networks have shared lanes for transit vehicles and private automobiles.

This study proposes a novel occupancy-based MP policy (OCC-MP) that combines passenger occupancies and vehicle queues when determining signal timings. By prioritizing movements with more queued passengers in the signal timing process, the movement of transit vehicles is implicitly prioritized over private automobiles since they typically carry more passengers. It also can provide priority to higher occupancy private automobiles if occupancy information of these vehicles is available. Unlike previous attempts to integrate TSP with MP, the proposed strategy can also be applied to networks with shared bus lanes (i.e., transit vehicles and private automobiles move in the same lanes). OCC-MP can also be applied in a partial CV environment, both when a subset of vehicles can be detected and when a subset can provide occupancy information to the signal controller. The performance of OCC-MP is shown to be robust to errors in passenger occupancy information from transit vehicles. Finally, a stability analysis demonstrates that the control policy has a larger stable region compared to rule-based MP that provides TSP.

The remainder of this paper is organized as follows. The next section provides an overview of the proposed OCC-MP control policy. This is followed by the simulation setup used to evaluate the performance of OCC-MP against baseline methods. Then, the results of the experiments are presented, including a comparative analysis between the proposed methods and the baseline approaches. The last section concludes the paper by highlighting the important findings and suggesting potential directions for future research.

METHOD

Max Pressure

Before the MP signal control is described, some notation is provided. Consider a network made up of links and intersections. Each link represents a directional road segment between two adjacent intersections. Upstream and downstream links at an intersection facilitate the movement of incoming and outgoing vehicles. Movement (l, m) represents the pair of links that serves vehicles from an upstream link l to a downstream link m. $U(i)$ denotes the set of all upstream links at intersection i, and $D(l)$ denotes the set of links downstream of link l. The proportion of traffic that turns from link l to link m is denoted by denoted by $r(l, m)$. The rate vehicles are allowed to pass through an intersection from link l to m per unit time is represented by the saturation flow, $c(l, m)$. Each intersection serves a set of signal phases denoted by Φ_i where each signal phase serves a set of vehicular movements. L_i^{ϕ} contains the set of movements served by phase ϕ at intersection i.

The MP algorithm involves three key steps;

1. Obtain the weights (w) of the movements. Weight is assigned to each movement by calculating the difference between the metric value of that movement and the average value of the metric for its downstream movements. This weight serves as an indicator of the level of congestion of both the upstream and downstream end of a movement.
2. Calculate the pressure (P) of phases using these weights. Pressure of each phase is calculated by summing up the weight multiplied by the associated saturation flow over all movements served by that phase. This is used to determine the relative importance of each phase served by the signal.
3. Select the phase (S) with maximum pressure. In acyclic MP algorithms, the phase with the highest pressure is activated in the next time step without regarding the sequence of phases. On the other hand, in cyclic MP algorithms, the green time for each phase in the next cycle is assigned proportionally based on the pressures of the respective phases in the designated phase sequence. The proposed model follows the former type.

Proposed OCC-MP policy

The original MP policy proposed in (*2*), referred to in this paper as the Q-MP, uses the number of queued vehicles on each link as the metric to determine which phase to activate. Thus, it treats both buses and private vehicles equally and disregards the fact that a bus can transport significantly more passengers compared to a single-occupant passenger vehicle. Consequently, in the Q-MP algorithm, the right of way may be assigned to a movement with five single-occupancy vehicles rather than a bus carrying fifty passengers. In contrast, traditional rule-based TSP algorithms (including that integrated with MP in (*47*)) prioritize bus movements at an intersection regardless of the level of congestion on adjacent links. This means that a bus with no passengers would be given the right of way over a conflicting movement with many queued vehicles posing the risk of a queue spillback.

To address these limitations, this study proposes an Occupancy-Based Max Pressure algorithm (OCC-MP). The proposed algorithm considers the average occupancy of the upstream movements in order to prioritize movements involving transit or high occupancy vehicles (HOVs). Specifically, the weight assigned to each movement is calculated as the product of the difference between the upstream and downstream queue lengths and the average occupancy upstream:

$$w(l,m) = o(l,m)[x(l,m) - \textstyle\sum_{n\in D(m)} x(m,n)r(m,n)]^+ = o(l,m)w_q(l,m)^+ \qquad (1)$$

where $o(l,m)$ is the average occupancy over all vehicles in movement (l,m); $x(i,j)$ is the number of vehicles queued on movement (i,j),, and the $+$ symbol around the square brackets denotes the maximum of either 0 or the value inside the square brackets. It is worth noting that the term in the square brackets is the weight of Q-MP, $w_q(l,m)$. An additional modification is made so that movements with negative weights that arise when downstream movements are more congested than the upstream queue, are forced to be 0. This is represented by the $+$ which has been used in prior studies and shown to improve network performance (*48*). Since all vehicles have an occupancy of at least 1, the average occupancy on a movement is a positive and bounded number. Therefore, the weight calculation in the OCC-MP algorithm is essentially a scaled-up version of the weight defined in the Q-MP algorithm.

At each update interval, the pressure of phase ϕ can be expressed as:

$$P^{\phi} = \sum_{(l,m)\in L_i^{\phi}} w(l,m) \times c(l,m) \times S(l,m),\ \forall \phi \in \Phi_i \tag{2}$$

Finally, the policy selects the phase with the maximum pressure in the set of all phases Φ_i (3). In this study, the signals are updated in the subsequent time step.

$$S^* = \arg\max_{\phi \in \Phi_i} P^{\phi} \tag{3}$$

The benefit of considering the average occupancy is that it allows the control policy to distinguish between movements that serve vehicles of higher occupancy and those that do not. In a simple example, Figure 1 shows a signalized intersection that serves two one-way movements with only private vehicles queued in the W-E direction while both private vehicles and a bus can be seen queued in the N-S direction. The N-S movement has 3 vehicles queued upstream and 2 vehicles downstream giving it a weight of $w_q(N,S) = (3-2) = 1$ under the Q-MP policy. However, the W-E movement has 5 queued vehicles on its upstream link and 2 vehicles downstream meaning its weight is $w_q(W,E) = (5-2) = 3$. Therefore, Q-MP prioritizes the W-E movement over the N-S movement. However, OCC-MP considers the occupancy of each queued vehicle on the upstream to calculate the average upstream occupancy giving the N-S movement a weight of, $w(N,S) = \frac{1+1+50}{3} \times (3-2) = 17.33$. The occupancy of the downstream vehicles is not considered when calculating the weight of the movement as a vehicle with a higher occupancy does not necessarily translate to less space available downstream. Interestingly, all vehicles on the upstream end of the W-E movement have the same occupancy, hence, the weight is similar to that of Q-MP, $w(W,E) = w_q(W,E) = \frac{1+1+1+1+1}{5} \times (5-2) = 3$. Therefore, OCC-MP prioritizes the N-S movement.

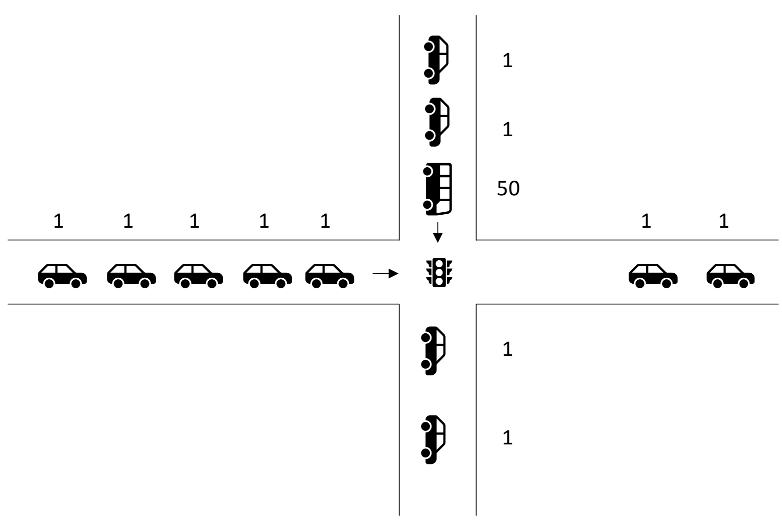


Figure 1. Example of transit signal priority using OCC-MP

Simply replacing the number of queued vehicles with the number of passengers on both upstream and downstream is not an effective mean of providing priority to high occupancy vehicles. The presence of downstream vehicles accounts for available storage space downstream. More waiting passengers downstream, specifically in buses, does not necessarily mean that the links have little capacity to accommodate vehicles from upstream links. Therefore, only the average upstream occupancy is considered. In cases where there are no vehicles downstream or in isolated intersections with no downstream movements, the weight of the movements in the OCC-MP algorithm is equal to the number of passengers upstream. For example, in Figure 1, if there were no vehicles downstream on either movement, $w(N,S)$ and $w(W,E)$ would represent the number of queued passengers on the N-S and the W-E movements respectively.

Since OCC-MP requires information on vehicle occupancy, it is assumed that the information is available to the controller. In scenarios where private vehicle occupancies are not readily available, an average occupancy value is assumed. However, in a fully connected vehicle environment, it is assumed that the occupancy information is readily accessible. On the contrary, many buses are equipped with Automatic Passenger Counting (APC) systems that allow real-time information of the number of passengers onboard a transit vehicle. Therefore, the exact bus occupancies are assumed to be available for calculation of weights.

Intersections where conflicting bus routes are served by different phases often receive simultaneous priority requests. Most prior studies have used either a first-come-first-serve or model-based methods (e.g., person-delay optimization, schedule-deviation minimization) to decide the sequence of phases at conflict intersections (*26*, *49–51*). These methods are subject to strict constraints that reduce the efficacy and increase the complexity of TSP control policies. The proposed OCC-MP handles conflict intersections much more efficiently without any additional constraints or assumptions. Specifically, if multiple buses are competing for right of way, OCC-MP selects the phase with the highest pressure considering the size of the queue on the link and the average occupancy of both buses and private vehicles. This way, OCC-MP is able to resolve conflicting bus movements at intersections without compromising the flow of private vehicles.

SIMULATION SETUP

To evaluate the effectiveness of the OCC-MP control strategy, simulation tests in the AIMSUN micro-simulation platform were performed. AIMSUN was chosen for its ability to realistically model traffic dynamics, such as congestion propagation, queue spillbacks, vehicle routing, and driving behavior(*52*).

Network setup

Simulation tests were carried out on an 8x8 grid network shown in Figure 2. While real-world street networks may not perfectly align with a square grid pattern, many urban networks exhibit grid-like characteristics. Previous studies that have simulated grid traffic networks reported results that can be generalized to more realistic networks (*53–57*). Road segments were categorized as arterials with mixed use that accommodate both private vehicles and buses. All road segments were assumed to have bi-directional traffic flow, with three travel lanes in each direction serving dedicated right, through and left movements at an approach (Figure 3). Each segment was 200 meters long with a capacity of 1800 vehicles per hour and a posted speed limit of 50 km/h. Within the network, all 64 intersections were signalized and consist of four phases, where through and right movements are served by one phase while left turning movements have a separate phase (Figure 3).

To simulate travel patterns and evaluate the effects of the proposed strategies, private vehicle origins and destinations were strategically positioned at the 32 entry and exit centroids located along the network's perimeter. A symmetric demand pattern was adopted, where the demand at North-South origin centroids was assumed to be twice the demand at East-West origin centroids. A two-hour peak period was simulated, consisting of gradually increasing private vehicle demand in 3-30 minute intervals, followed by a decrease in the last 30 minutes. This was then followed by a one-hour cooldown period. Two demand scenarios were tested: a high demand scenario with an average of 32,256 vehicles entering the network and a low demand scenario with an average of 23,040 entering vehicles (Figure 4). To model the private vehicle routing behavior, the study utilized the stochastic c-logit route choice model integrated within AIMSUN. This routing model aimed to replicate a stochastic user-equilibrium routing solution, where vehicles select routes at the beginning of a trip to minimize travel times.

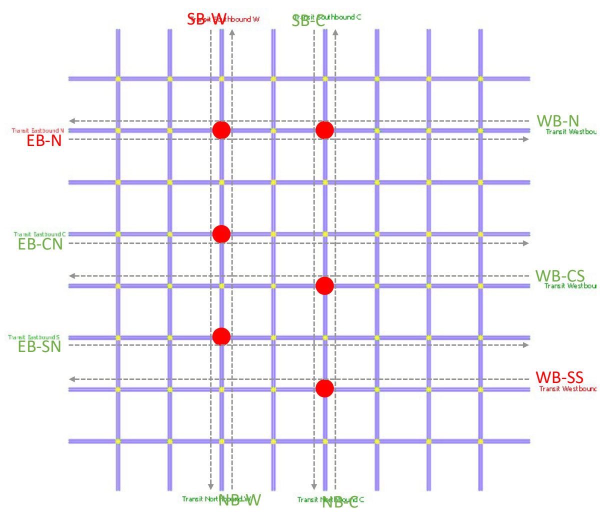


Figure 2. Network configuration

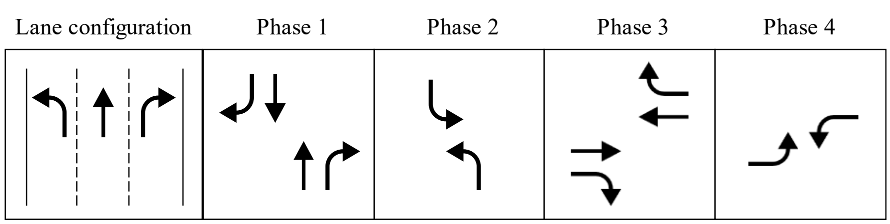


Figure 3. Lane configuration and phases

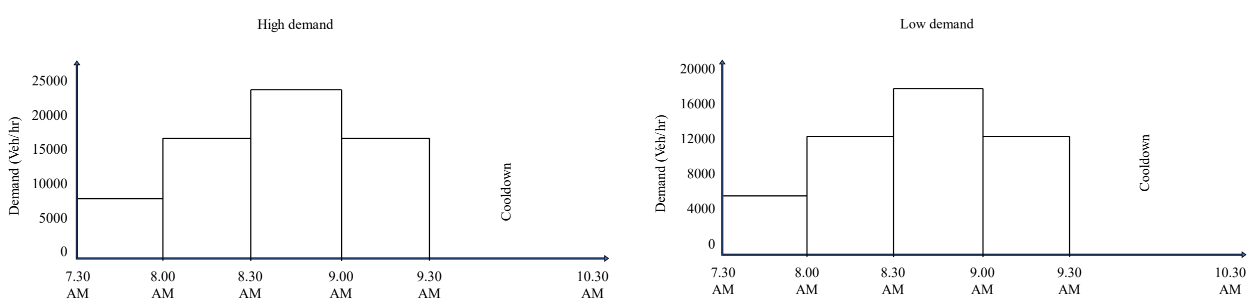


Figure 4. Time varied demand

The simulated network consists of ten bus routes, which include a combination of bi-directional and unidirectional routes; see Figure 2. Six of the routes operate between three pairs of O-D centroids, namely, (SB-W, NB-W), (SB-C, NB-C), and (EB-N, WB-N). These routes do not have conflicting movements and can be served by the same traffic signal phase. The remaining four routes, EB-CN, WB-CS, EB-SN, and WB-SS, are unidirectional, meaning that buses travel in only one direction. Within the network, there are seven high-occupancy routes indicated by green labels and three low-occupancy routes (marked with red labels) in Figure 2. The study simulates two different levels of passenger demand. In the high passenger demand scenario, the high occupancy routes are assigned an average occupancy of 50 passengers per bus, while the low occupancy routes have an average occupancy of 25 passengers per bus representing a situation where there is a substantial demand for public transportation. In contrast, the low passenger demand scenario assumes the high occupancy routes have an average occupancy of 12 passengers per bus, while the low occupancy routes have an average occupancy of 3 passengers per bus. This scenario represents a situation where there is less demand for public transportation, resulting in fewer passengers on the buses. Two levels of bus frequencies were also simulated where the headway between buses in the high frequency case was 2 minutes on average, while the low frequency case was simulated with a headway of 5 minutes between consecutive bus arrivals on each route.

The network includes six conflict intersections denoted by red circles in Figure 2 where buses may compete for right of way at the same time. As conflicting movements are served by different phases, the phase with a higher pressure will be allowed to move using the OCC-MP. To evaluate the control strategy under different bus demands, two different scenarios are considered: a high-demand case with an average headway of 2 minutes along all routes and a low demand case with an average headway of 5 minutes along all routes.

The performance of OCC-MP is compared with two other baseline policies. The first is the original Q-MP policy. The second baseline policy is an MP-based strategy that incorporates a rule-based transit signal priority, referred to as RB-MP. The RB-MP seeks to mimic the strategy proposed in (*47*). Specifically, it follows the MP framework to assign right of way based on vehicle queues; however, when a bus is detected, RB-MP overrides the original MP and assigns the right of way to serve bus movements in the next timestep. In the case of multiple buses approaching a conflict intersection, the right of way is assigned on a first-come-first-serve basis. To ensure consistency in the evaluation, all three MP control policies adopt a signal update interval of 10 seconds.

Scenario Setup

Different scenarios were simulated to understand the benefits and potential application of the proposed control policy.

Scenario 1 considers a situation where the system has no knowledge of private vehicle passenger occupancy. In this case, an average of 1.5 persons per private vehicle, as reported in (*58*), is assumed. However, the exact bus occupancies are assumed to be available from APC data. This scenario is further extended to test the resilience of the policy due to variations in the reported bus occupancies from APC. To test this, a random error term was added to the occupancies of buses reported to the controller after crossing every intersection. The error term was assumed to have a mean of 0, standard deviation of σ % of the mean occupancy at each intersection and additive over every intersection. Varying values of σ from 0 to 40 were tested to understand the impact of variations in APC data, and how it impacts the network performance.

Scenario 2 considers the case where individual vehicle occupancies are available to the signal controller, as would be possible in a connected vehicle (CV) environment. This means that the system has complete knowledge of both private vehicle and bus occupancies which is leveraged by the OCC-MP policy to calculate weights of movements based on their occupancy levels, dynamically. For the simulation, each private vehicle entering the network was randomly assigned an occupancy based on a probability distribution (shown in Table 1) such that the average private vehicle occupancy was approximately 1.5. In a fully connected environment, it is assumed that all vehicles are equipped with CV technology that is leveraged by the MP policies to accurately measure the queue lengths and (or) occupancies. However, in a real-world scenario, a network may have mixed flow comprising of both connected and non-connected vehicles. Therefore, a partially connected environment was also considered in which the CV penetration rate was varied from 20% to 100% to understand how the policies perform when limited information is available.

Table 1. Probability distribution of private vehicle occupancy

Occupancy	Probability
1	0.7
2	0.125
3	0.1
4	0.05
5	0.025

Within both scenarios, a total of 8 sub-scenarios were simulated, each representing a different combination of private vehicle demand, bus occupancy, and bus frequency. The private vehicle demand represents the overall traffic flow in the network, while the bus occupancy and frequency directly affect the bus operations and interactions with other vehicles. By considering both high and low occupancy levels and varying bus headways, the impact of different bus configurations on the performance of the policies can be analyzed. Table 2 contains the configuration of each sub-scenario. Each sub-scenario was simulated with 10 different random seeds to account for stochasticity and ensure robust analysis.

Table 2. Summary of sub-scenarios

Sub-Scenario	Private vehicle demand	Bus passenger demand	Bus Frequency
1	Low	High	High
2	Low	High	Low
3	Low	Low	High
4	Low	Low	Low
5	High	High	High
6	High	High	Low
7	High	Low	High
8	High	Low	Low

A final scenario was simulated to compare the stability of the control policies. Specifically, a certain private vehicle demand was simulated to see whether the number of vehicles in the network are bounded or keep growing. For this scenario, private vehicle demands were uniform throughout the 3 hours of the simulation, while buses arrived on each route with a constant headway of 2 minutes.

RESULTS

Scenario 1: Non-connected vehicle environment

To understand the level of congestion in the network, average network speeds under the Q-MP policy across the eight sub-scenarios are provided in Figure 5. The lines represent the mean value across all ten simulation iterations, while the shaded areas represent the confidence interval with +/- one standard error of observed values. Sub-scenarios with similar private vehicle and bus demands but different occupancies were grouped together as the Q-MP does not consider vehicle occupancies. As expected, the average network speeds drop drastically from about 25 km/h to just under 20km/h for the increase in private vehicle demand. A change in bus headway from 5 minutes to 2 minutes results in a slight decrease in network speeds, as expected.

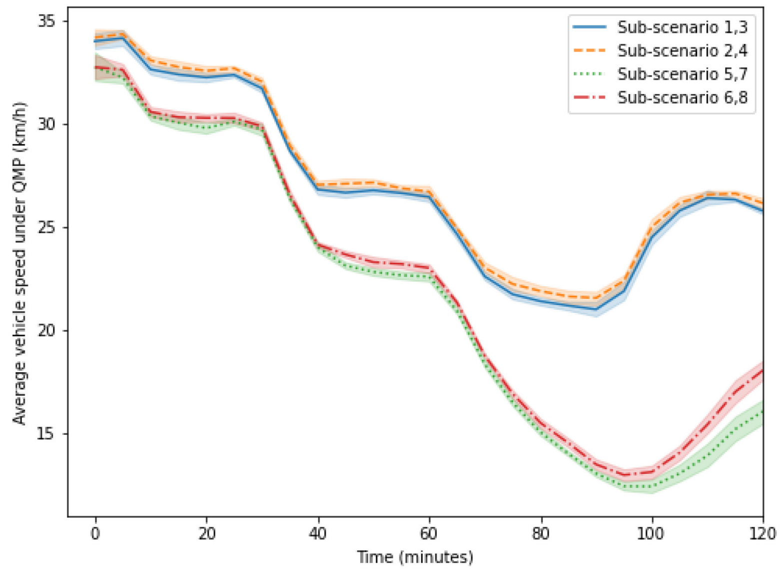


Figure 5. Average vehicle speeds under Q-MP across sub-scenarios

Vehicle travel time comparison

First, tests were conducted for $\sigma = 0$, which indicate that APC data from buses is perfectly accurate. Figure 6 presents the percentage change in vehicle travel time (VTT) of private vehicles under OCC-MP and RB-MP strategies, relative to the Q-MP. Standard errors across the ten simulation iterations are shown using whiskers. It is evident that integrating TSP using either the RB-MP or OCC-MP policies results in an increase in VTT of private vehicles over Q-MP. However, OCC-MP has a lower negative impact on private vehicles compared to RB-MP across all sub-scenarios.

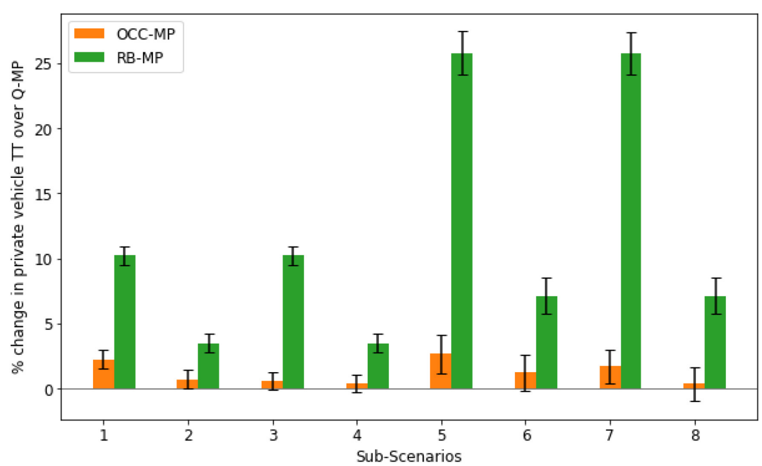


Figure 6. Percentage change in private vehicle travel time over Q-MP

It is expected that OCC-MP will behave similar to Q-MP when few buses are present; Sub-scenarios 3, 4, 6 and 8 confirm this as the confidence intervals designated by the standard errors contain 0, which suggests no statistically significant difference between the performance of OCC-MP and Q-MP. Sub-scenario 8, in which the demand for private vehicles was high and buses had a higher frequency and lower passenger occupancies, resulted in only 0.36% increase in private vehicle travel time. This can be attributed to the fact that there were fewer buses with lower occupancies in the network, leading OCC-MP to select similar phases to Q-MP. The maximum percentage change in VTT is 2.64% and observed for Sub-scenario 5, which has high bus frequency and passenger occupancy. In this sub-scenario, OCC-MP frequently selected phases to prioritize the movement of buses carrying more passengers. Note that RB-MP is not impacted by bus occupancies; thus, the same average VTTs were observed across pairs of sub-scenarios with the same vehicular demand. Overall, RB-MP resulted in statistically significant increases in VTT, ranging from 3.50% to 25.75%. Interestingly, the best performance of RB-MP is still worse than the worst performance of OCC-MP. This can be attributed to the fact that OCC-MP may select phases in which private vehicle queues are large, even when buses are present. These results highlight the effectiveness of the OCC-MP strategy in mitigating the negative impact on private vehicle travel times when compared to RB-MP.

To further demonstrate the difference in impacts to private vehicles across the three control strategies, Figure 7 plots the private VTT per minute. Notice that the private VTT continues to grow under the RB-MP policy despite the reduction in vehicle demand at the 90 minute mark. By contrast, the Q-MP and OCC-MP policies show travel time trends that reflect the level of vehicle demand. This finding is indicative of queue spillback phenomenon due to growing vehicle queues in the RB-MP policy.

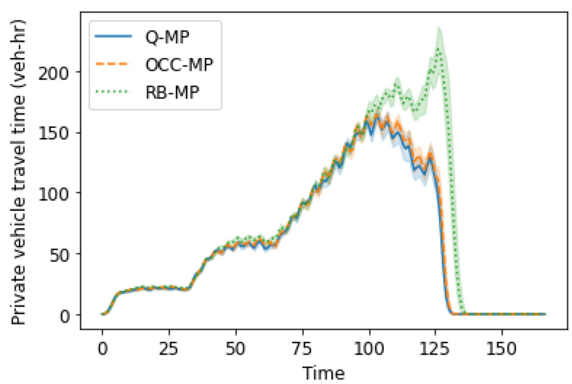


Figure 7. Total travel time of private vehicles (Sub-scenario 7)

Figure 8 illustrates the percent change in bus VTT under both OCC-MP and RB-MP compared to Q-MP. The results show that both strategies lead to a reduction in bus travel times compared to the baseline Q-MP strategy across all sub-scenarios, and all improvements are statistically significant. However, the magnitude of the improvement varies between the two strategies. As expected, RB-MP consistently outperforms OCC-MP and provides larger reductions in bus VTT since it provides full priority to buses. Specifically, OCC-MP achieves an average reduction in bus VTT of 14.5% when buses have higher occupancies (Sub-Scenarios 1, 2, 5 and 6) and 7.5% when buses are less crowded (Sub-Scenarios 3, 4, 7 and 8). This is expected as weights of bus movements are lower when there are fewer passengers onboard. Conversely, RB-MP shows little variation between the different sub-scenarios and achieves a nearly consistent average reduction of approximately 30% across all sub-scenarios.

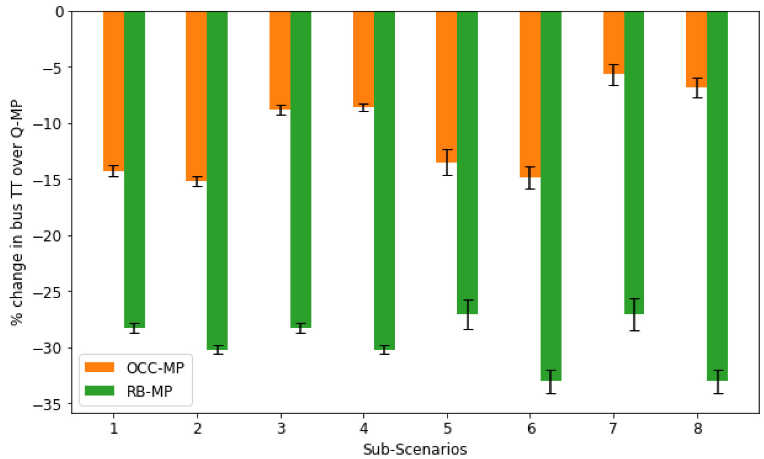


Figure 8. Percentage change in bus travel time over Q-MP

Passenger travel time comparison

Figure 9 compares the passenger travel times (PTT) of both OCC-MP and RB-MP strategies against Q-MP for all sub-scenarios. The results reveal that OCC-MP yields lower total PTT compared to Q-MP in 6 out of 8 sub-scenarios, indicating a positive impact on overall passenger mobility. The improvements range from approximately 0.1% to 3.6% on average, mostly in scenarios with higher bus occupancies. Maximum benefits were observed in Sub-scenario 1, suggesting OCC-MP best reduces overall passenger travel times when there are relatively fewer private vehicles and more buses carrying more passengers. Sub-scenarios 7 and 8 saw a nominal increase in passenger travel times by 0.9% and 0.1% respectively over Q-MP; however, the confidence intervals denoted by the standard errors reveal these increases are note statistically significant. Conversely, RB-MP shows mixed results with some sub-scenarios exhibiting improvements and others significant negative effects on PTT over Q-MP. Sub-scenarios 1 and 2 show improvements of 3.5% and 2.3% respectively, which were similar to OCC-MP in terms of PTT improvements. However, in the other sub-scenarios, RB-MP results in an increase in PTT ranging from approximately 1.9% up to 21.2% in Sub-Scenario 7. Previously it was found that Sub-Scenario 7 also corresponds to the highest increase in VTT of private vehicles and lowest bus VTT improvement compared to Q-MP. The finding highlights the superior performance of OCC-MP in balancing VTT of private vehicles and buses, ultimately resulting in lower passenger travel times.

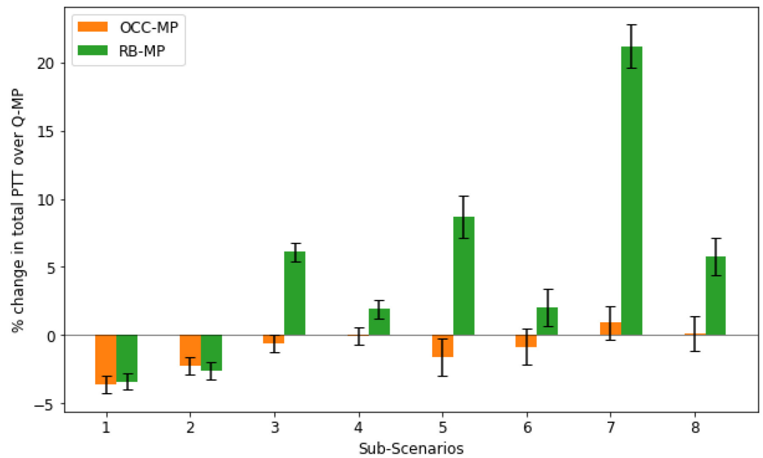


Figure 9. Percent change in passenger travel time over Q-MP

Sensitivity to variance of passenger occupancy

The proposed OCC-MP policy relies on accurate bus passenger occupancy for signal updates. To assess the policy's robustness against variation or inaccuracies in APC data, additional simulations were conducted for Sub-scenarios 1 and 3 in which the passenger occupancies provided to the control algorithm contained errors. Table 3a-b shows the VTT of private vehicles and buses and PTT as σ was increased from 0 to 40 at each intersection. The results indicate that there is relatively little variation observed across the network performance metrics. From Table 3a, it can be seen that the travel times of private vehicles, buses, and passengers in Sub-scenario 1 do not change significantly with σ. This suggests that OCC-MP performs reasonably well even when there is significant misreporting of bus occupancies, particularly for buses with high passenger demand. Sub-scenario 3 corresponds to a case with similar private vehicle and bus demand as Sub-scenario 1 but with fewer bus passengers. Therefore, it is expected that further underreporting of its occupancy may give it little to no priority over private vehicles resulting in higher travel times. Table 3b shows that variation of σ leads to slightly higher travel times than when $\sigma = 0$. However, all values except bus travel time at $\sigma = 40$ remain within one standard error of $\sigma = 0$, suggesting differences are not statistically significant. The consistency of the results indicates that the OCC-MP policy can effectively adapt to and optimize travel times under potential discrepancies in the APC data.

Table 3. Summary of network performance against variance in APC data

(a) Sub-scenario 1

	Private vehicle		Bus		All Passengers	
Percent variance, σ	Travel time (veh-hr)	Standard error	Travel time (veh-hr)	Standard error	Travel time (pax-hr)	Standard error
0%	2298.66	12.33	37.39	0.14	5035.75	24.06
10%	2294.46	10.74	37.21	0.13	5021.77	19.81
20%	2295.34	11.42	37.14	0.11	5020.11	20.42
30%	2299.86	11.13	37.09	0.08	5023.77	18.53
40%	2299.46	12.22	37.32	0.14	5034.65	23.16

(b) Sub-scenario 3

	Private vehicle		Bus		All Passengers	
Percent variance, σ	Travel time (veh-hr)	Standard error	Travel time (veh-hr)	Standard error	Travel time (pax-hr)	Standard error
0%	2260.89	10.06	39.79	0.10	3754.45	15.72
10%	2265.10	9.93	39.88	0.10	3761.63	15.56
20%	2263.54	10.54	39.81	0.09	3758.36	16.36
30%	2262.01	9.98	39.81	0.12	3756.06	16.04
40%	2269.44	10.80	39.93	0.10	3768.99	16.57

Scenario 2: Connected vehicle environment

Fully connected environment

The OCC-MP strategy was evaluated by simulating private vehicles with known occupancies and variable bus occupancies to understand how the control policy impacts travel time of non-transit HOVs. Since RB-MP does not differentiate vehicles by occupancy, it was not included in the analysis. Figure 10 presents a comparison of the percent change in PTT for OCC-MP over Q-MP for vehicles with different vehicle occupancies; values of 1 to 5 indicate private vehicles, while 6+ refers to buses. The results reveal that single occupant vehicles experience an increase in their travel times over the Q-MP. However, OCC-MP effectively prioritizes movements with higher occupancy vehicles, resulting in reduced travel times for those vehicles. Specifically, vehicles with an occupancy of 3 or more experience improvement in travel time in 5 out of 6 sub-scenarios. Interestingly, sub-scenarios with low private vehicle and bus demand (2 and 4), exhibit lower travel time for vehicles with occupancy of 2 and more, highlighting the positive impact of OCC-MP. By prioritizing HOV and buses even in mixed flow conditions without dedicated bus or HOV lanes, OCC-MP can serve as a strategic approach to discourage single-occupancy vehicles on the roads, promoting more efficient and sustainable transportation options.

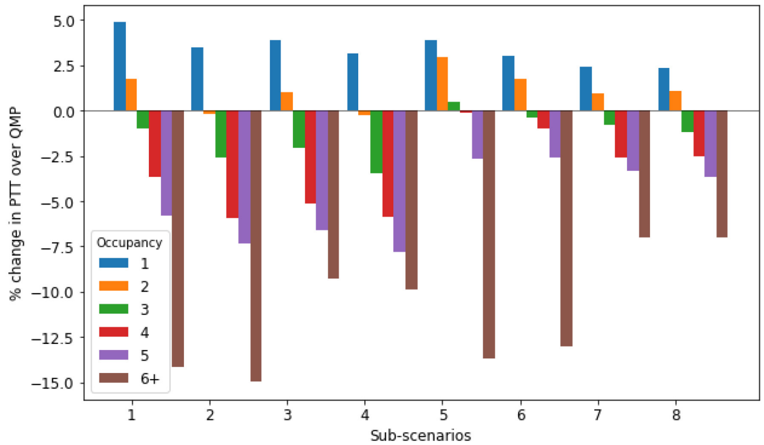


Figure 10. Percent change in passenger travel time over Q-MP by occupancy under OCC-MP

Partially connected environment

Although CV technology provides the potential to acquire detailed information from individual vehicles directly, implementation of a fully CV environment is farfetched. Therefore, the performances of the proposed OCC-MP policy and baseline methods were investigated under varying rates of CV penetration. In these tests, all control policies rely only on the information obtained from these CVs for measurement and updating the signal times.

Figure 11 shows the evolution of vehicle accumulation in the network for various CV penetration rates. The accumulation is highest for all three control policies when information from only 20% of the private vehicles is available. With increasing CV penetration rate, the number of queued vehicles in the network drops for all three policies resulting in lower congestion. Notice, however, the returns are diminishing with respect to CV penetration rate; i.e., the highest improvements are gained from increasing the penetration rate when the penetration rate is low. Note also that both Q-MP and OCC-MP have similar performance in terms of network congestion and show consistent reduction in vehicle accumulation with increasing CV penetration rate, while the RB-MP strategy consistently performs the worst.

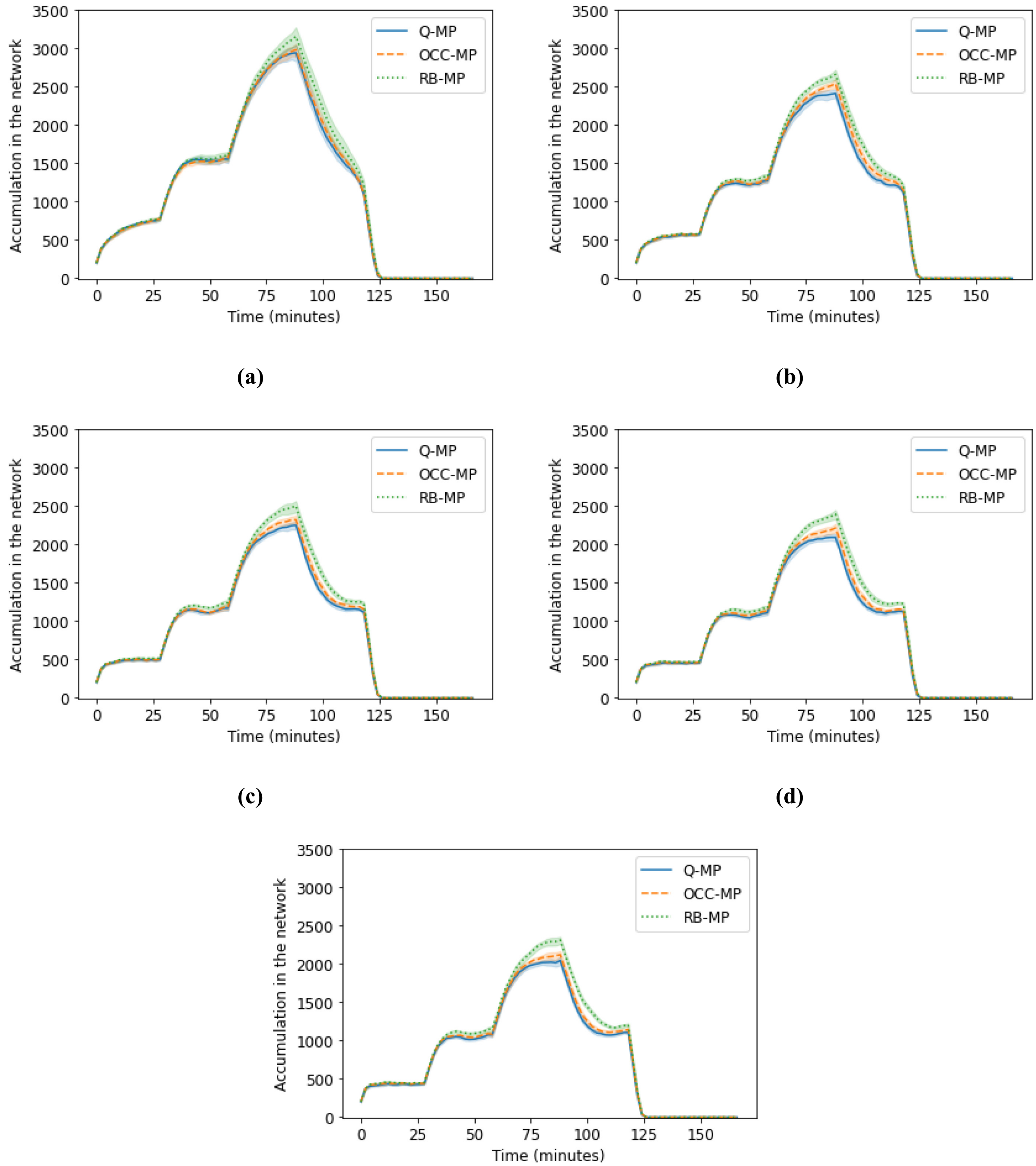


Figure 11. Accumulation of vehicles in the network for different CV penetration rates: (a) 20%; (b) 40%; (c) 60%; (d) 80%; (e) 100%

The performance of the control policies in terms of private VTT, bus VTT and total PTT is shown in Figure 12 for Sub-Scenario 1, which; was chosen because OCC-MP demonstrated the largest improvement in PTT. Overall, it is overserved that the increase in penetration rate of CVs improves the travel time of private vehicles and reduces the standard error across all policies, as more information becomes available on the actual queue lengths vehicle occupancy. The most significant improvements are observed for an increase in the penetration rate from 20% to 40%. This slowly diminishes as the penetration rate is further increased. RB-MP consistently demonstrates inferior performance compared to both Q-MP and OCC-MP. At 20% penetration rate, travel times of private vehicles under Q-MP and OCC-MP are statistically similar, but Q-MP further reduces travel times with the increase in CV penetration.

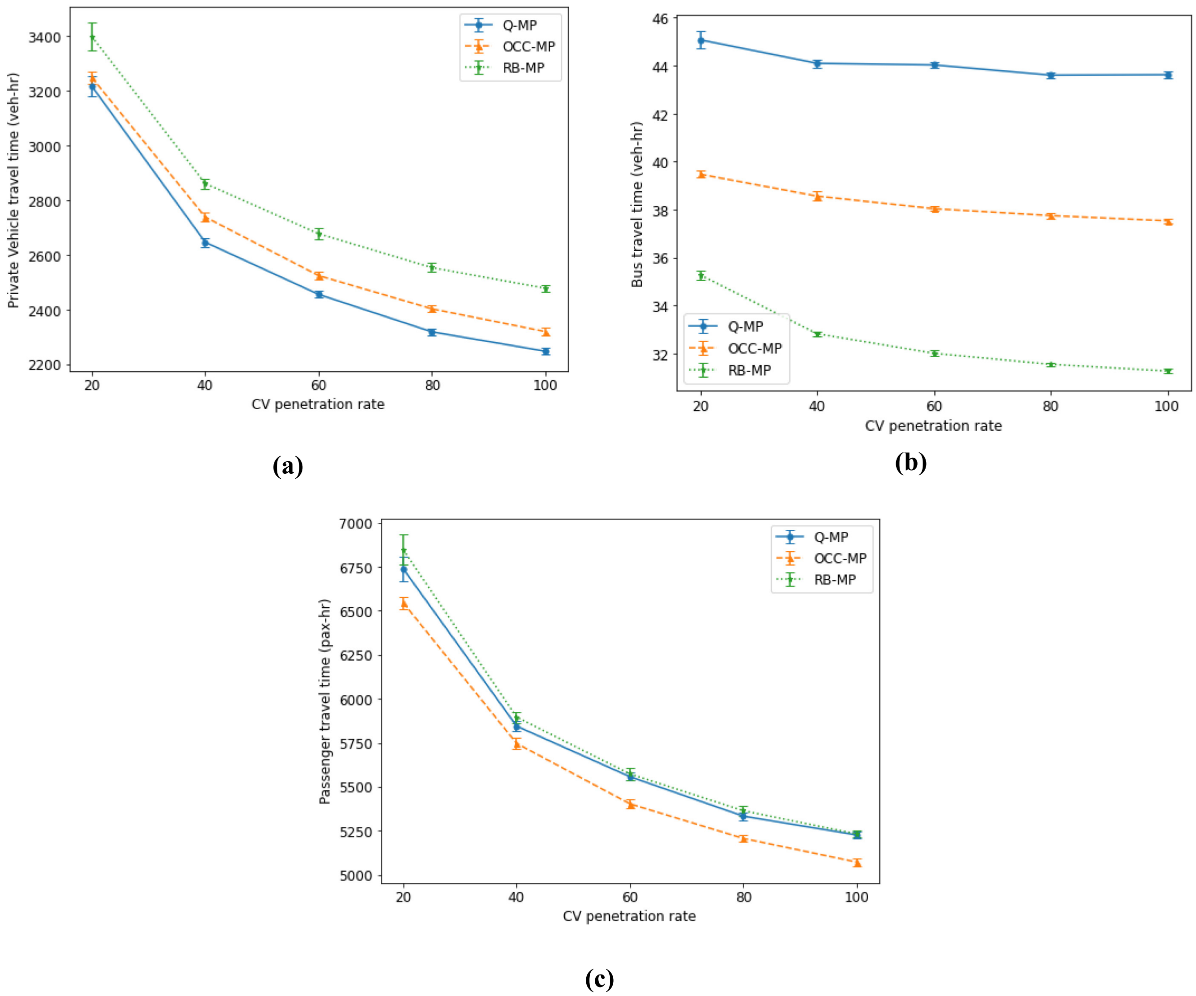


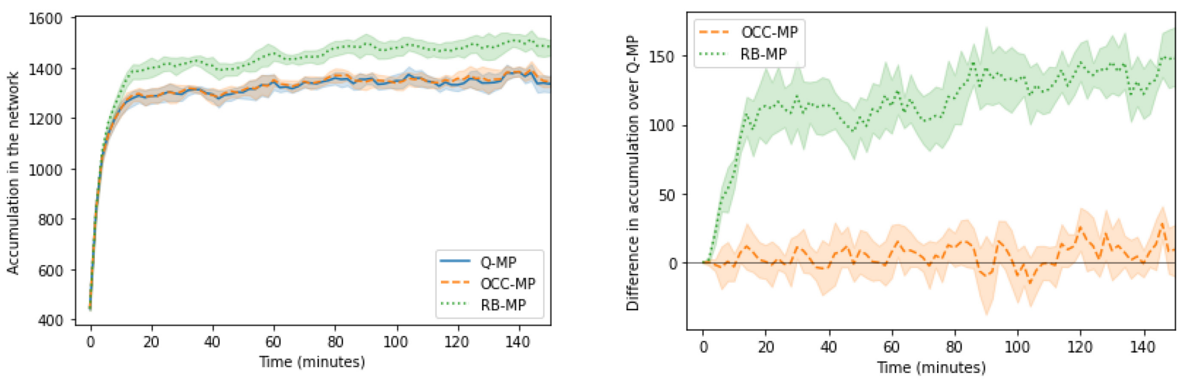
Figure 12. Effect of CV penetration rate on: (a) private vehicle travel time; (b) bus travel time; (c) passenger travel time

From Figure 12b, it is evident that bus VTT also improves as the percentage of connected vehicles in the network increases. Although there is a tradeoff between private vehicle and bus travel times, increasing CV penetration translates to lower congestion in the network (Figure 11), which in turn improves the overall bus operations. Note that these improvements are nominal for both Q-MP and OCC-MP, whereas larger improvements are observed for RB-MP with lower standard errors across the random seeds. Despite resulting in higher private vehicle and bus VTT compared to Q-MP and RB-MP policies, respectively, OCC-MP consistently resulted in the lowest PTT for all CV penetration rates (Figure 12c). Both the Q-MP and RB-MP have very similar performances in terms of PTT, with reductions that are smaller than that achieved by the OCC-

MP. The findings highlight the reliability of the proposed OCC-MP policy even when only a subset of the vehicles is connected.

Scenario 3: Stable region / Stable demand

Scenario 3 was used to evaluate the stability of the three control algorithms used in this study. Figure 13a shows the average accumulation (i.e., number of vehicles in the network) over time for a total entering demand of 40,500, vehicles (13,500 vehicles/hour). It is evident that the RB-MP policy leads to a larger number of vehicles in the network compared to both Q-MP and OCC-MP which have similar average accumulation throughout the simulation. Both Q-MP and OCC-MP policies also demonstrate a certain degree of stability as the average number of vehicles does not significantly grow over time. Figure 13b shows the difference in average accumulation in the network for OCC-MP and RB-MP compared to Q-MP. OCC-MP exhibits similar performance to Q-MP whereas, the rate of increase of vehicles in the network is much higher for RB-MP. This suggests that the RB-MP has a smaller stable region, while OCC-MP exhibits a similar stable region as Q-MP for private vehicles even while prioritizing buses.



(a) **(b)**

Figure 13. (a) Evolution of average accumulation in the network under different control policies (b) Difference in network accumulation over Q-MP

CONCLUSION

Conventional MP algorithms in existing literature rely on the measurement of vehicular metrics to update signal timings. These algorithms primarily prioritize maximizing throughput for private vehicles overlooking the impact on transit vehicles. However, this study introduces a novel approach by proposing an occupancy-based Max Pressure (OCC-MP) algorithm that considers the both the number of queued passengers and vehicles. By utilizing the average occupancy of vehicles queued upstream of an intersection, the control policy is able to improve passenger travel times and balance the performance of private vehicles and buses without constraints.

The performance of OCC-MP was tested against the original max pressure (Q-MP) and a rule-based MP algorithm that provides TSP (RB-MP). Micro-simulation tests on a grid network demonstrate that OCC-MP outperforms RB-MP in terms of reducing negative impacts on private vehicles while reducing bus VTT compared to Q-MP. Overall, OCC-MP results in lower PTT under various demand and occupancy levels. This is because OCC-MP not only prioritizes transit vehicles and those with higher occupancies, but also serves the movements with large private vehicle queues. The best performance was observed for lower private vehicle demand but more buses with higher occupancies. The control policy also demonstrates nominal variation in passenger travel time from errors in APC data highlighting the robustness of the algorithm. Further tests in a CV environment show that an increase in the penetration rate of CVs improve the overall performance of OCC-MP in reducing PTT. In a fully CV environment, OCC-MP consistently outperforms baseline methods in reducing the VTT of HOVs and buses making it a sustainable strategy to discourage single occupant vehicles in a transportation network without the need to implement expensive dedicated lane facilities. Finally, a stability analysis showed that OCC-MP has a stable region that is larger than the RB-MP policy. The average accumulation in the network was highest for RB-MP and kept growing over time. However, OCC-MP shows a stable region similar to that of Q-MP, suggesting the policy is able to handle larger private vehicle demand than RB-MP while providing priority to buses.

Although the simulations were conducted on a grid network, further research can explore the performance of OCC-MP in more complex urban networks. Since the applicability of the proposed OCC-MP encompasses mixed traffic, it may be interesting to explore its performance in networks with dedicated bus lanes or HOV lanes. Moreover, given the increasing emphasis on creating "complete streets" that accommodate various modes of transportation, future studies may consider developing MP control algorithms that consider the complexities of multimodal transport. It is worth noting that (*9*) demonstrated that different MP algorithms may have different optimal update intervals that maximize their performance. Therefore, the impact of optimal time-step for signal update interval can be explored for OCC-MP.

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AUTHOR CONTRIBUTIONS

The authors confirm contribution to the paper as follows: study conception and design: TA, HL, VG; analysis and interpretation of results: TA, HL, VG; draft manuscript preparation: TA, HL, VG. All authors reviewed the results and approved the final version of the manuscript.

REFERENCES

1. Tassiulas, L., and A. Ephremides. Stability Properties of Constrained Queueing Systems and Scheduling Policies for Maximum Throughput in Multihop Radio Networks. 1990.
2. Varaiya, P. Max Pressure Control of a Network of Signalized Intersections. *Transportation Research Part C: Emerging Technologies*, Vol. 36, 2013, pp. 177–195. https://doi.org/10.1016/j.trc.2013.08.014.
3. Levin, M. W. Max-Pressure Traffic Signal Timing: A Summary of Methodological and Experimental Results. *Journal of Transportation Engineering, Part A: Systems*, Vol. 149, No. 4, 2023. https://doi.org/10.1061/jtepbs.teeng-7578.
4. Le, T., P. Kovács, N. Walton, H. L. Vu, L. L. H. Andrew, and S. S. P. Hoogendoorn. Decentralized Signal Control for Urban Road Networks. *Transportation Research Part C:*

Emerging Technologies, Vol. 58, 2015, pp. 431–450. https://doi.org/10.1016/j.trc.2014.11.009.

5. Xiao, N., E. Frazzoli, Y. Li, Y. Wang, and D. Wang. Pressure Releasing Policy in Traffic Signal Control with Finite Queue Capacities. 2014.
6. Lioris, J., A. Kurzhanskiy, and P. Varaiya. Adaptive Max Pressure Control of Network of Signalized Intersections. *IFAC-PapersOnLine*, Vol. 49, No. 22, 2016, pp. 19–24. https://doi.org/10.1016/j.ifacol.2016.10.366.
7. Kouvelas, A., J. Lioris, S. A. Fayazi, and P. Varaiya. Maximum Pressure Controller for Stabilizing Queues in Signalized Arterial Networks. *Transportation Research Record: Journal of the Transportation Research Board*, Vol. 2421, No. 1, 2014, pp. 133–141. https://doi.org/10.3141/2421-15.
8. Liu, H., and V. V. Gayah. Total-Delay-Based Max Pressure: A Max Pressure Algorithm Considering Delay Equity. *Transportation Research Record: Journal of the Transportation Research Board*, 2023, p. 036119812211470. https://doi.org/10.1177/03611981221147051.
9. Liu, H., and V. V. Gayah. A Novel Max Pressure Algorithm Based on Traffic Delay. *Transportation Research Part C: Emerging Technologies*, Vol. 143, 2022, p. 103803. https://doi.org/10.1016/j.trc.2022.103803.
10. Mercader, P., W. Uwayid, and J. Haddad. Max-Pressure Traffic Controller Based on Travel Times: An Experimental Analysis. *Transportation Research Part C: Emerging Technologies*, Vol. 110, 2020, pp. 275–290. https://doi.org/10.1016/j.trc.2019.10.002.
11. Dixit, V., D. J. Nair, S. Chand, and M. W. Levin. A Simple Crowdsourced Delay-Based Traffic Signal Control. *PLoS ONE*, Vol. 15, No. 4, 2020. https://doi.org/10.1371/journal.pone.0230598.
12. Stephanedes, Y. J., and F. (eds.) Filippi. Transport Priority in Real-Time Traffic Control Systems. 1996.
13. Lin, Y., X. Yang, and N. Zou. Passive Transit Signal Priority for High Transit Demand: Model Formulation and Strategy Selection. *Transportation Letters*, Vol. 11, No. 3, 2019, pp. 119–129. https://doi.org/10.1080/19427867.2017.1295899.
14. Christofa, E., and A. Skabardonis. Traffic Signal Optimization with Application of Transit Signal Priority to an Isolated Intersection. *Transportation Research Record: Journal of the Transportation Research Board*, Vol. 2259, No. 1, 2011, pp. 192–201. https://doi.org/10.3141/2259-18.
15. Lin, Y., X. Yang, N. Zou, and M. Franz. Transit Signal Priority Control at Signalized Intersections: A Comprehensive Review. *Transportation Letters*, Vol. 7, No. 3, 2015, pp. 168–180. https://doi.org/10.1179/1942787514Y.0000000044.
16. Currie, G., and A. Shalaby. Active Transit Signal Priority for Streetcars. *Transportation Research Record: Journal of the Transportation Research Board*, Vol. 2042, No. 1, 2008, pp. 41–49. https://doi.org/10.3141/2042-05.

17. Truong, L. T., G. Currie, M. Wallace, C. De Gruyter, and K. An. Coordinated Transit Signal Priority Model Considering Stochastic Bus Arrival Time. *IEEE Transactions on Intelligent Transportation Systems*, Vol. 20, No. 4, 2019. https://doi.org/10.1109/TITS.2018.2844199.

18. Zeng, X., Y. Zhang, J. Jiao, and K. Yin. Route-Based Transit Signal Priority Using Connected Vehicle Technology to Promote Bus Schedule Adherence. *IEEE Transactions on Intelligent Transportation Systems*, Vol. 22, No. 2, 2021. https://doi.org/10.1109/TITS.2020.2963839.

19. Lee, J., A. Shalaby, J. Greenough, M. Bowie, and S. Hung. Advanced Transit Signal Priority Control with Online Microsimulation-Based Transit Prediction Model. 2005.

20. Lee, W. H., and H. C. Wang. A Person-Based Adaptive Traffic Signal Control Method with Cooperative Transit Signal Priority. *Journal of Advanced Transportation*, Vol. 2022, 2022. https://doi.org/10.1155/2022/2205292.

21. Liu, G., and T. Z. Qiu. Trade-Offs Between Bus and Private Vehicle Delays at Signalized Intersections: Case Study of a Multiobjective Model. *Transportation Research Record: Journal of the Transportation Research Board*, Vol. 2539, No. 1, 2016, pp. 72–83. https://doi.org/10.3141/2539-09.

22. Zhao, J., and X. Zhou. Improving the Operational Efficiency of Buses With Dynamic Use of Exclusive Bus Lane at Isolated Intersections. *IEEE Transactions on Intelligent Transportation Systems*, Vol. 20, No. 2, 2019, pp. 642–653. https://doi.org/10.1109/TITS.2018.2819243.

23. Zhao, J., and W. Ma. Optimizing Vehicle and Pedestrian Trade-Off Using Signal Timing in Intersections with Center Transit Lanes. *Journal of Transportation Engineering, Part A: Systems*, Vol. 144, No. 6, 2018. https://doi.org/10.1061/JTEPBS.0000145.

24. Ma, W., K. L. Head, and Y. Feng. Integrated Optimization of Transit Priority Operation at Isolated Intersections: A Person-Capacity-Based Approach. *Transportation Research Part C: Emerging Technologies*, Vol. 40, 2014, pp. 49–62. https://doi.org/10.1016/j.trc.2013.12.011.

25. Christofa, E., K. Ampountolas, and A. Skabardonis. Arterial Traffic Signal Optimization: A Person-Based Approach. *Transportation Research Part C: Emerging Technologies*, Vol. 66, 2016, pp. 27–47. https://doi.org/10.1016/j.trc.2015.11.009.

26. Christofa, E., I. Papamichail, and A. Skabardonis. Person-Based Traffic Responsive Signal Control Optimization. *IEEE Transactions on Intelligent Transportation Systems*, Vol. 14, No. 3, 2013, pp. 1278–1289. https://doi.org/10.1109/TITS.2013.2259623.

27. Zeng, X., X. Sun, Y. Zhang, and L. Quadrifoglio. Person-Based Adaptive Priority Signal Control with Connected-Vehicle Information. *Transportation Research Record: Journal of the Transportation Research Board*, Vol. 2487, No. 1, 2015, pp. 78–87. https://doi.org/10.3141/2487-07.

28. Li, J., Y. Liu, H. Yang, and B. Chen. Bus Priority Signal Control Considering Delays of Passengers and Pedestrians of Adjacent Intersections. *Journal of Advanced Transportation*, Vol. 2020, 2020, pp. 1–12. https://doi.org/10.1155/2020/3935795.

29. Christofa, E., and A. Skabardonis. Traffic Signal Optimization with Application of Transit Signal Priority to an Isolated Intersection. *Transportation Research Record: Journal of the Transportation Research Board*, Vol. 2259, No. 1, 2011, pp. 192–201. https://doi.org/10.3141/2259-18.

30. Ding, J., M. Yang, W. Wang, C. Xu, and Y. Bao. Strategy for Multiobjective Transit Signal Priority with Prediction of Bus Dwell Time at Stops. *Transportation Research Record: Journal of the Transportation Research Board*, Vol. 2488, No. 1, 2015, pp. 10–19. https://doi.org/10.3141/2488-02.

31. Lee, W.-H., and H.-C. Wang. A Person-Based Adaptive Traffic Signal Control Method with Cooperative Transit Signal Priority. *Journal of Advanced Transportation*, Vol. 2022, 2022, pp. 1–17. https://doi.org/10.1155/2022/2205292.

32. Chen, Y.-H., Y. Cheng, and G.-L. Chang. Incorporating Bus Delay Minimization in Design of Signal Progression for Arterials Accommodating Heavy Mixed-Traffic Flows. *Journal of Intelligent Transportation Systems*, Vol. 27, No. 2, 2023, pp. 187–216. https://doi.org/10.1080/15472450.2021.2002149.

33. Yu, Z., V. V. Gayah, and E. Christofa. Implementing Phase Rotation in a Person-Based Signal Timing Optimization Framework. 2018.

34. Yu, Z., V. V. Gayah, and E. Christofa. Person-Based Optimization of Signal Timing. *Transportation Research Record: Journal of the Transportation Research Board*, Vol. 2620, No. 1, 2017, pp. 31–42. https://doi.org/10.3141/2620-04.

35. Wu, K., M. Lu, and S. I. Guler. Modeling and Optimizing Bus Transit Priority along an Arterial: A Moving Bottleneck Approach. *Transportation Research Part C: Emerging Technologies*, Vol. 121, 2020, p. 102873. https://doi.org/10.1016/j.trc.2020.102873.

36. Wu, K., and S. I. Guler. Estimating the Impacts of Transit Signal Priority on Intersection Operations: A Moving Bottleneck Approach. *Transportation Research Part C: Emerging Technologies*, Vol. 105, 2019, pp. 346–358. https://doi.org/10.1016/j.trc.2019.06.003.

37. Yang, T., and W. (David) Fan. Evaluation of Transit Signal Priority at Signalized Intersections under Connected Vehicle Environment. *Transportation Planning and Technology*, Vol. 46, No. 2, 2023, pp. 145–159. https://doi.org/10.1080/03081060.2023.2176308.

38. Ghanim, M. S., and G. Abu-Lebdeh. Real-Time Dynamic Transit Signal Priority Optimization for Coordinated Traffic Networks Using Genetic Algorithms and Artificial Neural Networks. *Journal of Intelligent Transportation Systems*, Vol. 19, No. 4, 2015, pp. 327–338. https://doi.org/10.1080/15472450.2014.936292.

39. Long, M., X. Zou, Y. Zhou, and E. Chung. Deep Reinforcement Learning for Transit Signal Priority in a Connected Environment. *Transportation Research Part C: Emerging Technologies*, Vol. 142, 2022, p. 103814. https://doi.org/10.1016/j.trc.2022.103814.

40. Guo, G., and Y. Wang. An Integrated MPC and Deep Reinforcement Learning Approach to Trams-Priority Active Signal Control. *Control Engineering Practice*, Vol. 110, 2021, p. 104758. https://doi.org/10.1016/j.conengprac.2021.104758.

41. Alizadeh Shabestray, S. M., and B. Abdulhai. Multimodal INtelligent Deep (MiND) Traffic Signal Controller. 2019.

42. Ling, K., and A. Shalaby. Automated Transit Headway Control *via* Adaptive Signal Priority. *Journal of Advanced Transportation*, Vol. 38, No. 1, 2004, pp. 45–67. https://doi.org/10.1002/atr.5670380105.

43. Yang, K., M. Menendez, and S. I. Guler. Implementing Transit Signal Priority in a Connected Vehicle Environment with and without Bus Stops. *Transportmetrica B: Transport Dynamics*, Vol. 7, No. 1, 2019, pp. 423–445. https://doi.org/10.1080/21680566.2018.1434019.

44. Hu, J., B. B. Park, and Y.-J. Lee. Coordinated Transit Signal Priority Supporting Transit Progression under Connected Vehicle Technology. *Transportation Research Part C: Emerging Technologies*, Vol. 55, 2015, pp. 393–408. https://doi.org/10.1016/j.trc.2014.12.005.

45. Hu, J., Z. Zhang, Y. Feng, Z. Sun, X. Li, and X. Yang. Transit Signal Priority Enabling Connected and Automated Buses to Cut Through Traffic. *IEEE Transactions on Intelligent Transportation Systems*, Vol. 23, No. 7, 2022, pp. 8782–8792. https://doi.org/10.1109/TITS.2021.3086110.

46. Chen, X., X. Lin, M. Li, and F. He. Network-Level Control of Heterogeneous Automated Traffic Guaranteeing Bus Priority. *Transportation Research Part C: Emerging Technologies*, Vol. 140, 2022, p. 103671. https://doi.org/10.1016/j.trc.2022.103671.

47. Xu, T., S. Barman, M. W. Levin, R. Chen, and T. Li. Integrating Public Transit Signal Priority into Max-Pressure Signal Control: Methodology and Simulation Study on a Downtown Network. *Transportation Research Part C: Emerging Technologies*, Vol. 138, 2022. https://doi.org/10.1016/j.trc.2022.103614.

48. Gregoire, J., X. Qian, E. Frazzoli, A. de La Fortelle, and T. Wongpiromsarn. Capacity-Aware Backpressure Traffic Signal Control. *IEEE Transactions on Control of Network Systems*, Vol. 2, No. 2, 2015, pp. 164–173. https://doi.org/10.1109/TCNS.2014.2378871.

49. Hu, J., B. B. Park, and Y.-J. Lee. Transit Signal Priority Accommodating Conflicting Requests under Connected Vehicles Technology. *Transportation Research Part C: Emerging Technologies*, Vol. 69, 2016, pp. 173–192. https://doi.org/10.1016/j.trc.2016.06.001.

50. Ma, W., Y. Liu, and X. Yang. A Dynamic Programming Approach for Optimal Signal Priority Control Upon Multiple High-Frequency Bus Requests. *Journal of Intelligent Transportation Systems*, Vol. 17, No. 4, 2013, pp. 282–293. https://doi.org/10.1080/15472450.2012.729380.

51. Head, L., D. Gettman, and Z. Wei. Decision Model for Priority Control of Traffic Signals. *Transportation Research Record: Journal of the Transportation Research Board*, Vol. 1978, No. 1, 2006, pp. 169–177. https://doi.org/10.1177/0361198106197800121.

52. Barceló, J., and J. Casas. Dynamic Network Simulation with AIMSUN. In *Simulation Approaches in Transportation Analysis*, Springer, Boston, pp. 57–98.

53. Bayrak, M., Z. Yu, and V. V. Gayah. A Population-Based Incremental Learning Algorithm to Identify Optimal Location of Left-Turn Restrictions in Urban Grid Networks. *Transportmetrica B: Transport Dynamics*, Vol. 11, No. 1, 2023, pp. 528–547. https://doi.org/10.1080/21680566.2022.2102553.

54. Mazloumian, A., N. Geroliminis, and D. Helbing. The Spatial Variability of Vehicle Densities as Determinant of Urban Network Capacity. *Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences*, Vol. 368, No. 1928, 2010, pp. 4627–4647. https://doi.org/10.1098/rsta.2010.0099.

55. Knoop, V. L., S. P. Hoogendoorn, and J. W. C. Van Lint. Routing Strategies Based on Macroscopic Fundamental Diagram. *Transportation Research Record: Journal of the Transportation Research Board*, Vol. 2315, No. 1, 2012, pp. 1–10. https://doi.org/10.3141/2315-01.

56. Ortigosa, J., and M. Menendez. Traffic Performance on Quasi-Grid Urban Structures. *Cities*, Vol. 36, 2014, pp. 18–27. https://doi.org/10.1016/j.cities.2013.08.006.

57. Ortigosa, J., V. V. Gayah, and M. Menendez. Analysis of One-Way and Two-Way Street Configurations on Urban Grid Networks. *Transportmetrica B: Transport Dynamics*, Vol. 7, No. 1, 2019, pp. 61–81. https://doi.org/10.1080/21680566.2017.1337528.

58. Schrank, D., B. Eisele, and T. Lomax. 2021 Urban Mobility Report. *Texas A&M Transportation Institute*, No. June, 2021.