DEPARTMENT OF TRANSPORTATION

# Understanding Risks and Opportunities for Ramp Metering Control in a Mixed-Autonomy Future

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Vehicle automation may change traffic flow dynamics. This will also impact the control of traffic flow via infrastructure-based systems such as ramp metering control. In this work we investigated the impact that different levels of automation and connectivity will have on ramp metering control, and proposed modifications to existing ramp metering algorithms to improve their performance under different automation scenarios. We find that low-level automation such as adaptive cruise control may decrease mainline throughput by up to 58% on average and increase travel time by 61%. However, full connectivity and automation may decrease travel time by up to 40%. Based on these potential impacts, modifications to the ramp metering algorithm settings were developed for each of the seven automation scenarios. These modifications are shown to improve operations in each scenario.

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# Understanding risks and opportunities for ramp metering control in a mixed-autonomy future

# Final Report

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# List of Abbreviations

ACC - Adaptive cruise control
ATT - Average travel time
AQL - Average queue length
AV- Autonomous vehicles
AVG - Average
CACC – Connected adaptive cruise control
HV - Human-driven vehicles
LOS - Level of service
ML – Mainline (highway)
MnDOT – Minnesota Department of Transportation
MPR - Market penetration rate
R - Ramp
SUMO - Simulation of Urban Mobility
TP – Throughput
TT - Travel time
Traci - Traffic Control Interface

# Executive Summary

Vehicle automation has the potential to substantially change traffic flow dynamics and thus influence the effectiveness of traffic control methods such as ramp metering that rely on a specific traffic flow behavior. Such changes in flow, and the resulting changes in the efficacy of ramp metering, may result either from more efficient flow (e.g., with connected and fully automated vehicles) or less efficient flow (e.g., with lower-level automation scenarios such as adaptive cruise control). As a global leader in both the development and deployment of ramp metering control, Minnesota is well positioned to investigate the challenges posed by varying degrees of vehicle automation — from low-level systems like adaptive cruise control (ACC) to fully automated vehicles — on ramp metering control efficacy.

This study focuses on understanding how different vehicle automation scenarios, including market penetration rates of both current and proposed automated vehicles, will influence ramp metering strategies. We will explore modifications to these strategies to maintain or enhance their effectiveness in scenarios characterized by increased autonomy. This includes addressing potential safety hazards associated with mixed-autonomy traffic flows, such as faster queue propagation and increased risk of rear-end collisions, which may be exacerbated by ACC vehicles that tend to exaggerate braking events.

A detailed simulation analysis was conducted to investigate both how different types of vehicle automation impacted the efficacy of ramp metering, as well as what small modifications should be made to ramp metering to allow it to be as effective as possible, given the degree and type of automation on the roadway.

The findings show that the increased prevalence of automation will either decrease the efficiency or leave unused capacity on the road, depending on the type of automation. In either case, adjustments to the ramp metering timing, based on the traffic flow makeup, are able to overcome the decrease in performance. Based on the findings of this work, it is possible that straightforward adjustments to the current ramp metering algorithm timing could be sufficient to avoid some of the deterioration in performance, although other ramp metering algorithms may be able to outperform this algorithm in the future.

The outcomes of this research provide crucial insights into the long-term implications of vehicle automation on traffic management in Minnesota. By evaluating different automation scenarios, we develop engineered solutions that accommodate varying levels of vehicle automation, ensuring the safety and efficiency of ramp metering strategies as traffic dynamics evolve.

# Chapter 1: Introduction

Vehicle automation and connectivity have the potential to dramatically alter the fundamental dynamics of traffic flow. This is true both for fully automated vehicles as well as for vehicles with partial automation technology such as adaptive cruise control (ACC) that are already commercially available today. By changing the dynamics of traffic flow, these emerging technologies will also influence the efficacy of traffic flow-based control strategies such as ramp metering. As one of the leading deployments of ramp metering globally, Minnesota roadways may see a substantial change in the efficacy of ramp metering strategies as traffic dynamics change.

With this motivation in mind, this study answers how ramp metering strategies employed in Minnesota could be influenced by different vehicle automation scenarios such as automated vehicle market penetration rates both for proposed, fully automated vehicles and currently available low-level automated vehicles. This study develops strategies to keep Minnesota ramp meters effective under scenarios with increased autonomy. Furthermore, under the new traffic flow-density relationship that is emerging in a mixed autonomy traffic flow, queues may propagate at a higher speed, since ACC vehicles have been shown to exaggerate braking events. This may increase the risk of rear-end collisions. However, vehicles equipped with emergency brake assist features might be able to mitigate this risk.

## 1.1 Initiative Advantages

Based on the MnDOT Research Steering Committee Criteria in Table 1, this study has two primary benefits: operations/maintenance savings by providing an understanding of how driver assist technologies such as ACC and other vehicle automation technologies will impact traffic flow management; and technology benefits by providing an understanding of how new technologies could change traffic flow on Minnesota roads.

**Table 1. MnDOT Research Steering Committee Benefits Summary.**

| Benefit Category | Applicable | Can quantify | How benefits are quantified |
|---|---|---|---|
| Construction Savings | | | |
| Decreased engineering cost | | | |
| Environmental aspects | | | |
| Improved lifecycle costs | | | |
| Operation/maintenance saving | X | Yes | Increased traffic flow efficiency can be measured as increased bottleneck capacity. |
| Reduce risk | | | |
| Reduce road user cost | | | |
| Safety | | | |
| Technology | X | No | No direct way to measure, but addresses how technology will change MN roadways. |

## 1.2 Operation/maintenance savings

This planned work provides benefits to improved MnDOT operations by investigating how the introduction of different vehicle automation technologies such as low-level automation (adaptive cruise control) and full automation might impact traffic flow dynamics at merge bottlenecks, and how this could impact the efficiency of current ramp metering strategies. Additionally, this proposal will consider what modifications should be made to existing ramp metering algorithms to make them effective for future generation traffic dynamics. This has the potential to lead to future operation savings since effective ramp metering reduces the need for other operational measures.

## 1.3 Technology

The research will study how new driving technologies such as adaptive cruise control and vehicle automation will impact traffic on Minnesota roads. This is an important step to understanding how technology will impact traffic flow in Minnesota. Studying this will provide benefits by allowing agencies such as MnDOT to prepare for the widespread use of new driver assist and automated driving technologies.

# Chapter 2: Methodology

## 2.1 Site selection

Sites are selected to reflect a range of ramp metering scenarios and locations in the Twin Cities Metro area. This includes sites with a variety of mainline freeway lanes and on-ramp lanes. All sites selected currently operate with ramp metering.

For each site, digital scoping is conducted using Google Maps to identify the site characteristics and the suitability of the site for the simulation study. The proposed study sites and backup sites are presented in Table 2 below.

**Table 2. Selected on-ramp sites for simulation.**

| Site No. | Longitude | Latitude | Major Rd | Minor Rd | Direction | Highway lanes | Ramp lanes | Map link |
|---|---|---|---|---|---|---|---|---|
| **1** | 44°59'36.0"N | 93°27'32.5"W | I-494 | County Rd 6 | SB | 3 | 1 | I-494 & County Rd 6, Plymouth |
| **2** | 44°50'24.7"N | 93°17'55.6"W | I-35W | W 90th St | SB | 3 | 1 | I-35W & W 90th St, Bloomington |
| **3** | 45°02'00.9"N | 92°58'57.2"W | I-694 | E Country Line Rd | EB | 2 | 1 | I-694 & E Country Line Rd, Oakdale |
| **4** | 45°03'59.8"N | 93°14'41.6"W | I-694 | NE Central Ave | EB | 3 | 1 | I-694 & NE Central Ave, Fridley |
| **5** | 45°07'21.9"N | 93°03'01.1"W | I-35E | Ash St | SB | 2 | 1 | I-35E & Ash St, White Bear Lake |

## 2.2 Proposed vehicle types

In this study, we are modeling Four vehicle types, namely: human-driven vehicles (HVs), currently-available low-level automated vehicles, specifically commercially available adaptive cruise control (ACC) vehicles, fully automated vehicles (AVs), and connected adaptive cruise control (CACC) vehicles (or CAVs) that could be available in the near future. Each vehicle type has unique driving behavior that could alter the emergent properties of traffic flow in different ways. To develop relevant automation scenarios, it's important to clearly define our study vehicles in terms of commonly used definitions for levels of vehicle automation.  For this, we frame the three proposed vehicle types in terms of the commonly used Society of Automotive Engineers (SAE) levels of automation (SAE, 2018).

These levels are used to categorize vehicles based on the extent to which they can operate without human intervention. There are six levels of automation defined by SAE, ranging from no automation (level 0) to full automation (level 5). Table 3 provides a brief description of each SAE level along with how each correlate to the vehicle types in our study.

**Table 3. SAE levels of automate tracker is ion and associated study vehicle definitions.**

| Automation Level | Description | Study Definition |
|---|---|---|
| Level 0: No Driving Automation | The driver is responsible for all aspects of driving. | HV |
| Level 1: Driver Assistance | The vehicle has one automated feature, such as adaptive cruise control or lane-keeping assistance, but the driver is still responsible for most aspects of driving. | ACC |
| Level 2: Partial Driving Automation | The vehicle has at least two automated features that work together, such as adaptive cruise control and lane-keeping assistance. The driver is still responsible for monitoring the road and being ready to take control if needed. | ACC |
| Level 3: Conditional Driving Automation | The vehicle can handle most aspects of driving in certain conditions, such as on a highway with clear lane markings, but the driver may need to take control in certain situations. | AV |
| Level 4: High Driving Automation | The vehicle can handle all aspects of driving in most situations, but the driver may need to take control in exceptional circumstances. | AV |
| Level 5: Full Driving Automation | The vehicle can handle all aspects of driving in all situations, and there is no need for a driver to be present. | AV |

Human-driven vehicles fall into SAE level 0, as they do not have any automated driving features. The driver is responsible for all aspects of driving, including steering, acceleration, and braking.

ACC vehicles are typically categorized as level 1 or 2, depending on their automation capabilities. Level 1 ACC vehicles have one automated feature, such as adaptive cruise control, that can assist with maintaining a safe following distance from the vehicle in front. Level 2 ACC vehicles have at least two automated features that work together, such as adaptive cruise control and lane-keeping assistance, but still require the driver to be alert and ready to take control if needed.

Fully automated vehicles and CACC vehicles fall into SAE levels 3 to 5, depending on their capabilities. Level 3 vehicles can handle most aspects of driving in certain conditions, such as on a highway with clear lane markings, but the driver may need to take control in certain situations. Level 4 vehicles can handle all aspects of driving in most situations, but the driver may need to take control in exceptional circumstances. Level 5 vehicles can handle all aspects of driving in all situations, and there is no need for a driver to be present.

Categorizing the vehicles into SAE levels as described above is important for the literature review, as SAE is a standard used by many to categorize levels of vehicle automation. During the literature review process, SAE level 0 was taken as HVs, SAE levels 1-2 were taken as ACCs, and SAE levels 3-5 were taken as Avs and CACCs. To capture these unique behaviors, we rely on microscopic traffic flow models to describe the dynamics of these Four vehicle types.

## 2.3 Car-following models

Car-following models are used to describe the longitudinal dynamics of a following vehicle based on the response to the vehicle in front. While a variety of car-following models exist, the general form is described in Equation 1, where $\ddot{x}_i(t)$is the acceleration of vehicle i at time t, $s_i(t)$ is the spacing gap between the front bumper of vehicle i and the rear bumper of vehicle i-1 at time t, $v_i(t)$ is the velocity of vehicle i at time t, and $\dot{s}_i(t)$ is the relative speed between vehicle i and vehicle i-1 at time t. An illustration is presented in Figure 1.

$$\ddot{x}_i(t) = f(s_i(t), v_i(t), \dot{s}_i(t) \quad (1)$$

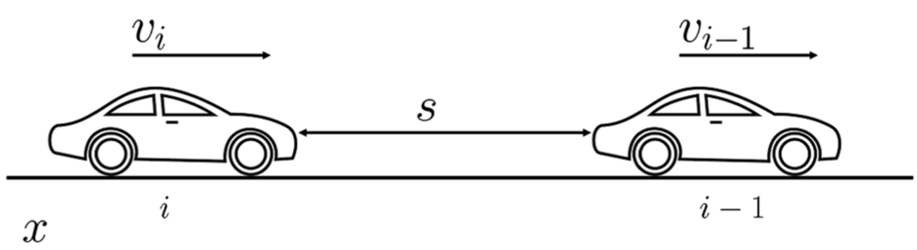


**Figure 1. Car following behavior between vehicle i and vehicle i-1.**

### 2.3.1 Car-following model selection

Over the last several decades, many different variations of microscopic car-following models have been developed. Some of these models include the Gipps model (Gipps, 1981), the Optimal Velocity model (OVM) (Bando et al., 1995), the Gazis-Herman-Rothery (GHR) model (Chandler et al., 1958), and the Intelligent Driver model (IDM) {Treiber et al., 2000), among others. In this study, the IDM is selected to model all traffic types (human, ACC, and AV). The IDM has been widely employed in the transportation research community to model traffic flow due to its good performance as shown by Calvert et al. (2017); James et al. (2019); and Talebpour & Mahmassani (2016). Furthermore, the model has been implemented in many of the prevailing microsimulation software packages including VISSM, AIMSUN, and SUMO.

The IDM framework is described in Equations 2 and 3. The state variables $\ddot{x}$, $\dot{s}$, s, and v are described above. There are a total of 6 model parameters, where a is the maximum acceleration ($m/s^2$), b is the maximum deceleration ($m/s^2$), $v_0$ is the desired speed (m/s), $s_0$ is the minimum spacing gap (m), δ is the acceleration exponent, and $\tau$ is the time gap (s). The model parameters are defined in Table 4.

Because each vehicle type has different dynamics, unique parameter sets are defined for each. The parameter $v_0$ is set to the site speed limit for each vehicle type as this represents the vehicle's desired speed. A discussion on parameter selection for each vehicle type is provided below.

$$\ddot{x} = a(1 - \left(\frac{v}{v_0}\right)^{\delta} - \left(\frac{\hat{s}(v,\dot{s})}{s}\right)^{2}) \tag{2}$$

$$\hat{s}(v,\dot{s}) = s_0 + \tau v - \frac{v\dot{s}}{2\sqrt{ab}} \tag{3}$$

**Table 4. IDM parameter values for each vehicle type.**

| Vehicle Type | a [m/s$^2$] | b[m/s$^2$] | $V_0$ [m/s] | $S_0$ [m] | $\delta$ | $\tau$ [s] |
|---|---|---|---|---|---|---|
| Human | 1.06 | 1.11 | 44.10 | 3.40 | 4.00 | 1.26 |
| ACC | 0.60 | 5.20 | 44.10 | 6.30 | 15.50 | 2.20 |
| AV | 1.70 | 2.00 | 44.10 | 2.50 | 4.00 | 1.00 |
| CACC | 3.80 | 4.50 | 44.10 | 0.50 | 4.00 | 0.60 |

### 2.3.2 HV parameters

The task of modeling HVs has been a research focus for several years (Hamdar et al., 2008; Shang & Stern, 2020), and while many models exist, in this study we choose the IDM model as it has been shown to accurately reproduce human driver behavior (Kesting & Treiber, 2008; Shang & Stern, 2020). The specific parameter values are presented by Kesting & Treiber (ibid), which were calibrated based on experimentally collected field data. These parameters were chosen because they were calibrated with naturalistic driving data. Although a wide range of driving behaviors can be present among different types of drivers, we believe these parameter values can approximate the driving behaviors of humans.

### 2.3.3 ACC Parameters

While the IDM was originally developed to model HVs, there is a long history of using the IDM to model both automated and partially automated vehicles (Calvert et al., 2017; James et al., 2019; Talebpour & Mahmassani, 2016), and we adopt it in this study to model the longitudinal dynamics of ACC vehicles. The parameter values for the ACC described in Table 4 were calibrated from experimental data collected through a series of car-following experiments conducted by Gunter et al. (2020). Like the HV model, this model is not hypothetical and captures the car-following dynamics of ACC vehicles available today.

These experiments were conducted with seven commercially available ACC vehicles labeled A-G on both the minimum and maximum following settings for each vehicle. The experiments are conducted as a two-vehicle test where a lead vehicle drives with a pre-specified velocity profile and a test vehicle follows with ACC engaged. The velocity and spacing profiles are recorded using high-accuracy GPS.

Using the experimental data described above, De Souza and Stern (2021) calibrated the IDM parameters by minimizing the spacing error between the experimental data and the simulated model data. They found that the IDM could accurately predict the driving behavior of ACCs. In this study, we adopt the parameter values for vehicle A on the maximum following setting that was calibrated by De Souza and Stern (ibid).

### 2.3.4 AV and CACC Parameters

While the HV and ACC vehicle parameters were calibrated with real experimental trajectory data, this is not possible for Avs and CACC vehicles as they are not yet commercially available, therefore determining appropriate parameter values is a challenging task. To distinguish between the longitudinal behavior of ACCs, AVs, and CACCs, we consider the difference between how each vehicle type may impact the traffic flow.

One important property of traffic flow is string stability, which tells whether small perturbations from an equilibrium flow where all vehicles in a platoon drive with no acceleration will amplify or dissipate as they propagate from one vehicle to the next along a string of vehicles. String stability is an aggregate-level property of traffic flow, that depends on the microscopic (vehicle-level) behavior of each vehicle in the traffic stream. While there is no proven analytical relationship between string stability and highway throughput, practically speaking, Shang and Stern found that string stable flow tends to correlate with an increase in highway throughput (Shang & Stern, 2021). Prior studies have shown that both HVs and ACCs tend to be string unstable (De Souza & Stern, 2021; Sugiyama et al., 2008).

Although AVs and CACC vehicles are not currently available, they will most likely behave differently than today's ACC vehicles in a variety of ways, including both longitudinal and lateral control. In order to achieve full autonomy, vehicles will see technological improvements in sensing and actuation from ACCs today. With these technological improvements, a likely scenario is that AVs and CACC vehicles will achieve string stability and potentially increase highway throughput. Therefore, in this study, CACC vehicles and AVs are modeled so that they are string stable, unlike HVs or AVs.

We adopt theoretical IDM parameter values for AVs from Kesting et al*.* (2008). The IDM is chosen to model AV vehicles because each model parameter is physically interpretable which is important when a lack of data is available for parameter calibration. These parameters have been employed by Talebpour & Mahmassani (2016) to simulate the dynamics of AVs, in which they found the AVs to be string stable, the scenario we are interested in modeling in this study.

Regarding CACC vehicles, there are limited studies focusing on the car-following model parameters. However, the IDM model parameters shown in Table 4 are obtained from the work of Lu et al. (2018) and represent one possible set of driving behaviors for CACC vehicles. Since these parameter values are speculative, the results that are derived from simulations using these parameter values are also speculative and simply serve as one possible outcome of traffic flow with CACC vehicles (or CAVs). These parameters emulate connectivity by reducing the following gap and delay between vehicles, as would be expected with connectivity.

## 2.4 Lane changing model selection

In this study, we adopt the LC2013 lane-changing model developed by Erdmann . This model is currently implemented in SUMO and has been used widely to model the lateral dynamics of both human and automated vehicles (Kavas-Torris et al., 2021; Shang & Stern, 2021). The model considers four different lane-changing motivations, namely: (i) strategic change (change lanes to reach the next edge on the vehicle's route), (ii) cooperative change (change lanes to help other vehicles), (iii) tactical change (change lanes to avoid following a slow vehicle), (iv) regulatory change (in jurisdictions with right-handed driving, clear the left-lane if not being used for an overtaking maneuver).

The complete formulas and decision trees used in implementation are omitted for brevity, but the general framework is as follows: for every time step and for every vehicle (i) compute the best lanes, (ii) compute the safe velocities in the current lane considering the speed at the previous simulation step, (iii) compute the best lane changing action (move left, move right, stay), (iv) execute lane change if it is safe and desirable. For more details, we direct the reader to Erdmann (2015).

As with the car-following model, we define unique parameter sets for each vehicle type. The relevant parameter values and their descriptions are provided in Table 5, and a discussion on parameter selection follows.

**Table 5. LC2013 parameter values and descriptions for each vehicle type.**

| Parameter | Value (HV) | Value (ACC) | Value (AV and CACC) | Description |
|---|---|---|---|---|
| lcStrategic | 1.0 | 1.0 | 3.0 | Eagerness for performing strategic lane-changing where higher values result in earlier lane-changing. [0-inf] |
| lcCooperative | 1.0 | 1.0 | 1.0 | Willingness for performing cooperative lane changing, where lower values result in reduced cooperation. [0-1] |
| lcSpeedGain | 1.0 | 1.0 | 5.0 | Eagerness for performing lane changing to gain speed, where higher values result in more lane-changing. [0-inf] |
| lcKeepRight | 1.0 | 1.0 | 1.2 | Desire to keep right, where higher values result in earlier lane-changing. [0-inf] |
| lcLookAheadLeft | 2.0 | 2.0 | 3.0 | Factor for configuring the strategic lookahead distance when a change to the left is necessary. [0-inf] |
| lcSpeedGainRight | 0.1 | 0.1 | 0.1 | Factor for configuring the threshold asymmetry when changing to the left or to the right for speed gain. By default, changing right takes more deliberation and a value of 1.0 achieves symmetry. [0-inf] |
| lcAssertive | 5.0 | 5.0 | 5.0 | Willingness to accept lower front and rear gaps on the target lane. The required gap is divided by this value. [positive real numbers] |

### 2.4.1 HV and ACC parameters

The parameters used to model HV's lane-changing behavior are the default parameters employed in SUMO, which were developed to model human driving behavior. The ACC parameters are the same as the HV parameters because ACC vehicles still require humans to determine lane-changing behavior. These parameters have been employed by Shang & Stern (2021) to model both HVs and ACCs.

### 2.4.2 AV and CACC parameters

The parameter values for AVs are adopted from Kavas-Torris et al. (2021). The authors considered a wide range of lane-changing models along with the way AVs have been modeled in other microsimulation software packages such as VISSM, to determine which parameters in the LC2013 model could affect AV lane-changing behavior. The authors then alter these identified parameter values to reflect the difference between HV and AV lane-changing behavior. For CACC vehicles, we assumed lane-changing behavior similar to AVs. Since CACC vehicles are expected to change lanes earlier than HVs to position themselves optimally, their connectivity enables a faster and safer lane-changing process. The same behavior is also expected from AVs.

The lcStrategic and lcSpeedGain parameters are increased due to the fact AVs will likely have a larger desire to make strategic lane changes and lane changes to gain speed. The lcLookAheadLeft parameter is also increased because AVs are expected to have a longer horizon when it comes to look ahead distance necessary for lane-changing, meaning they could change lanes before encountering a slowdown in their current lane. Furthermore, the lcKeepRight parameter is increased as it is expected AVs will change lanes earlier than HVs would in order to keep in the right lane. The lcSpeedGainRight, and lcCooperative values were not changed but were deemed relevant. The lcCooperative parameter is also kept constant at the maximum value as it is expected AVs will be able to take part in cooperative lane changing as HVs do. Finally, the lcSpeedGainRight parameter is constant as it is expected AVs will generally follow the same roadway conventions as HVs and prefer to use the left lane for speed gain lane-changing maneuvers.

Initial simulations revealed that most lane-changing parameters in SUMO have minimal or negligible impacts on simulation dynamics. However, the parameter "lcAssertive" (denoting a vehicle's willingness to accept reduced gaps on the target lane) emerged as an exception. To rectify this, we adjusted this parameter from its default value of 1 to 5 for all vehicle types. This adaptation was necessary due to the conservative gap acceptance approach in the default model. This conservative approach led to two primary issues: 1) incoming ramp vehicles faced difficulties merging and became trapped at the end of the acceleration lane; 2) lane utilization in the merging section exhibited disparities, with the inner lane experiencing high congestion while the outer lane maintained nearly free-flow conditions. Consequently, the adjustment facilitates smooth merging for ramp vehicles and ensures balanced lane usage in the merging section, leading to more accurate and realistic behavior.

## 2.5 Literature Review on Automation Scenarios

In recent years, there has been a growing interest in the deployment of automated vehicles, which have the potential to improve road safety, reduce traffic congestion, and increase mobility for various groups of people. As a result, many parties have attempted to forecast the future market penetration rates of automated vehicles.

To investigate likely AV adoption scenarios, we refer to a recent systematic review of passenger vehicle automated deployment timelines (Agrawal et al., 2023). The authors conduct a systematic literature review of both past and current AV deployment timelines from various stakeholder groups including government organizations, private stakeholders, and research organizations. Table 6 summarizes some of their key findings on AV fleet size predictions along with some additional sources not considered in their review (denoted with *).

**Table 6. Review of AV fleet size predictions.**

| Citation | Timeline | SAE Level [Study Vehicle] | Prediction |
|---|---|---|---|
| IEEE (2012) | 2040 | 4 or 5 [AV] | 75% |
| Townsend (2014) | 2030 | 4 [AV] | 25-35% |
| Kyriakidis et al. (2015) | 2050 | 5 [AV] | 50% |
| Simons et al. (2018) | 2022 - 2050 | 4 or 5 [AV] | 10-80+% |
| Talebian & Mishra (2018) | 2050 | 4 or 5 [AV] | 15-100% |
| Yankelevich et al. (2018) | 2028 | 4 [AV] | 20% |
| Concas et al. (2019) | 2030 - 2050 | 4 or 5 [AV] | 18.5-50% |
| Ksenofontov & Milyakin (2020) | 2045 | 5 [AV] | 2-22% |
| Carlier, M. (2025) | 2030 | 4 or 5 [AV] | 10% |
| Mishra et al. (2025) | 2050 | 4 [AV] | 55-83% |
| Litman (2025)* | 2030 - 2060 | 4 or 5 [AV] | 0 -50% |

As shown in Table 6, the AV fleet size predictions vary considerably and there is no clearly accepted opinion about what percentage of vehicles will be AVs in the near future. Unlike AVs, ACC vehicles are currently available and about 92% of new vehicles today have ACC available (*Consumer reports,* 2024, Feb. 14). Although most new vehicles today have ACC equipped, it is unclear what percentage of the total vehicle fleet has ACC available and what percent has it actively engaged.

Despite the growing interest in automated vehicles and the large number of studies that have been conducted on the topic, it is still not clear what the levels of automation will look like in the next 5-15 years. There are many factors that could influence the adoption rate of automated vehicles, including technological advancements, regulatory policies, and consumer preferences. Therefore, it is important to consider a wide range of automation scenarios when evaluating the potential impacts of automated vehicles on-ramp meter efficiency.

## 2.6 Automation Scenarios

For the reasons described earlier, in our study, we propose several different automation scenarios, which reflect different potential market penetration rates of human-driven (HV), ACC, and fully automated vehicles (AVs), based on different potential adoption scenarios. These scenarios range from a low level of automation, with mostly human-driven vehicles on the road, to a high level of automation, with a majority of vehicles being fully automated. We also consider a scenario in which only CACC vehicles exist. Given their inherent connectivity, we assume that all vehicles are connected to each other, with no unconnected vehicles present. The proposed automation scenarios are presented in Table 7.

**Table 7. Proposed Automation Scenarios**

| Scenario | Percent HV | Percent ACC | Percent AV | Percent CACC |
|---|---|---|---|---|
| 1: Full HV (Baseline) | 100 | 0 | 0 | 0 |
| 2: Full ACC | 0 | 100 | 0 | 0 |
| 3. Full AV | 0 | 0 | 100 | 0 |
| 4. High HV | 70 | 30 | 0 | 0 |
| 5. High ACC | 30 | 60 | 10 | 0 |
| 6 . High AV | 20 | 20 | 60 | 0 |
| 7. Full CACC | 0 | 0 | 0 | 100 |

Scenarios 1-3 represent uniform traffic scenarios, where we can investigate the impacts of HV, ACC, and AV independently. Scenario 1 (100% HV) serves as the baseline. It's also important to consider mixed traffic behavior, and how the interplay between HV, ACC, and AV dynamics will impact ramp meter efficiency. This is represented by scenarios 4- 6, with various combinations representing high HV, high ACC, and high AV scenarios.

# Chapter 3: Simulation setup

In this chapter, we describe the simulation configuration, the evaluation metrics, and important modeling assumptions. Simulations are conducted at five candidate sites, shown in Table 2.

## 3.1 Simulation Configuration

The simulations are performed using SUMO along with the Traci (Traffic Control Interface) framework. SUMO is a well-established open-source traffic simulation tool that allows users to model urban road networks, traffic flows, and various vehicle behaviors realistically. Traci complements SUMO by providing a real-time interface to control and modify the simulation during runtime, enabling us to dynamically adjust the ramp metering algorithm based on current traffic conditions. An example of the SUMO GUI for Site 5 is provided in Figure 1.

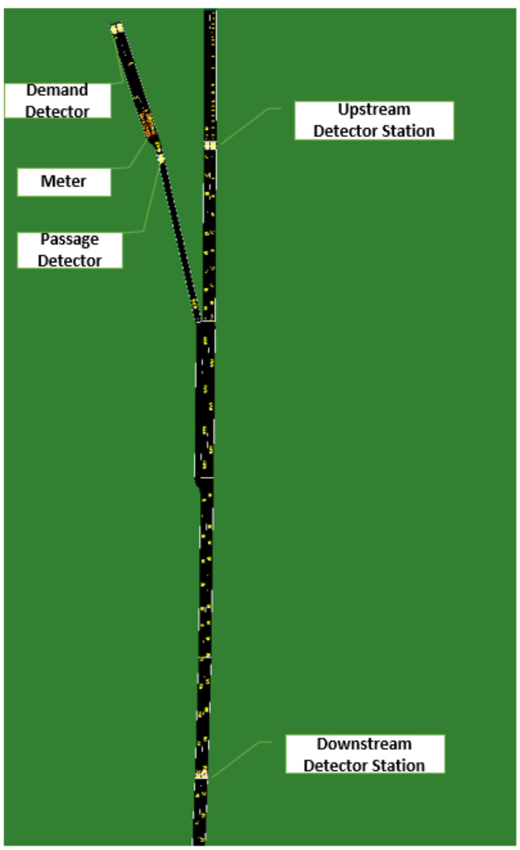


**Figure 2. SUMO GUI for Site 5, with meter, demand, passage, and mainline detectors are shown.**

First, the geometries of the five selected sites are configured in SUMO, including lane geometry, detector locations, and meter location, as depicted in Figure 2.  Real peak-hour volumes for each site are modeled using MnDOT's data extract tool. The microscopic models for each vehicle type are utilized and the peak hour volume is distributed to each vehicle type depending on the automation scenario tested Finally, MnDOT's Density Adaptive Metering Algorithm is implemented in Python for each site, including all metering phases, rate limits, mainline segment density determination, and release rate calculations described in the Density Adaptive Metering pdf provided by MnDOT.

## 3.2 Experiment and Evaluation Metrics

Each simulation is carried out for 3,600 seconds. All five sites are tested with each automation scenario. Throughput (TP) and average travel time (ATT) are two metrics used to evaluate mainline traffic conditions at an analysis zone. This analysis zone starts at the downstream detector and extends 5000 m upstream to ensure the full length of traffic congestion could be fully encapsulated. The ATT is given by Equation 1, where $i$ is an index denoting a single vehicle that passed through the analysis zone, $ATT$ is the average travel time (seconds), $TT_i$ is, and $N$ is total number of vehicles that passed through the analysis zone during the simulation.

$$ATT = \frac{\sum_{i=1}^{N} TT_i}{N} \qquad (1)$$

The TP is given by Equation 2, where $TP$ is the throughput (veh/hr) and $T$ is the analysis time period.

$$TP = \frac{N}{T} \qquad (2)$$

To evaluate the ramp queue conditions, we considered average wait times and queue lengths. Throughout the simulation, cumulative demand and passage counts are collected and updated every 30 seconds. Using these values, the average queue length (AQL) is calculated as shown in Equation 3, where $j$ is an index representing the discrete 30-second interval; $D_j$ is the cumulative demand at interval $j$; $P_j$ is the cumulative passage at interval $j$; $J$ is the total number of discrete intervals; $AQL$ is the average queue length in vehicles.

$$AQL = \frac{\sum_{j=1}^{J} (D_j - P_j)}{J} \qquad (3)$$

The average wait time (AWT) is given by Equation 4, where $\Delta t$ is the length of the discrete interval $j$ (30 seconds). This approximates the area between the passage and demand curves (total wait time) divided by the total number of vehicles processed by the queue.

$$AWT = \frac{\sum_{j=1}^{J} (D_j - P_j)\Delta \mathrm{t}}{P_J} \qquad (4)$$

## 3.3 Modeling Assumptions

Several assumptions are integrated into the modeling process. First, the merging length for ramp vehicles is extended to 100 m at each site. This extension ensures that ramp vehicles are able to merge smoothly onto the mainline without becoming immobilized at the end of the acceleration lane. Additionally, we assume that ACC vehicles drive under human control until 300 m after successfully merging onto the mainline, at which point the drivers activate the ACC function. Thus, in the simulation, ramp vehicles initially adhered to a microscopic human vehicle (HV) model, transitioning to a microscopic ACC model at a point 300 m downstream from the merge.

For MnDOT's Density Adaptive Metering algorithm, although the mainline zone is inherently adaptive, the modeling simplified this by establishing a fixed zone bounded by the immediate upstream detector and the nearest downstream detector of the meter. This zone is presumed to represent the segment with the highest mainline density, given the absence of other modeled on-ramps. Additionally, the simulation omits the incorporation of demand undercount correction and queue backup limits. To avert scenarios involving ramp queue spillover, the ramp storage length is artificially extended which allows for the quantification of the complete ramp queue. Notably, although the simulation's ramp queue length was manipulated, the algorithm’s minimum release rate continued to be grounded in the actual ramp geometry.

# Chapter 4: Simulation results

In this chapter, we present and discuss preliminary simulation results for both mainline and ramp queue conditions under the described automation scenarios with MnDOT's Density Adaptive Metering Algorithm.

## 4.1 Mainline Results

The findings regarding mainline throughput and travel time are visually presented in Figure 3 and Figure 4. As depicted in Figure 3, scenarios involving full HV and AV operation showcase notably superior throughput compared to scenarios involving fully commercially available ACC vehicles. This trend holds true across all examined sites. A similar trend is evident within the mixed-autonomy scenarios, where scenarios with high levels of HV and AV automation demonstrate improved throughput when compared to their high ACC counterparts.

However, it is observed that the Full CACC scenario performs significantly better than all other automation scenarios. Since these results appear speculative, we set them aside and focus on comparing the outcomes among other automation scenarios.

Figure 4 offers insight into the overall trends in mainline travel time. Generally, the full HV scenarios tend to yield the shortest travel times. The full AV scenarios display relatively similar performance to full HV scenarios, although a few exceptions are noted at Sites 1 and 5, where they exhibit slightly higher travel times. The full ACC scenarios show a significant increase in travel times at almost all sites in comparison to the full HV and AV scenarios. However, an exception exists at Site 1, where the full ACC travel time is unexpectedly lower than that of the full AV scenario.

Within mixed-autonomy scenarios, the trend is somewhat nuanced. Typically, the high HV scenarios result in the lowest travel times, except for a slight deviation at Site 2, where the high AV scenario displays marginally lower values. The high AV scenarios generally entail slightly longer travel times compared to high HVs, but they still outperform the travel times associated with high ACC scenarios. Several exceptions emerge, particularly at Sites 4 and 5, where the high AV scenarios demonstrate slightly higher travel times than the high ACC scenarios.

In summary, while there are a few exceptional cases, the overarching theme is clear: scenarios featuring full or high HV and AV automation tend to outperform their full or high ACC counterparts. However, the Full CACC scenario stands out with superior performance in both throughput and travel time, reinforcing its potential advantages. Given that these results seem speculative, we set them aside and primarily compare the remaining automation scenarios."

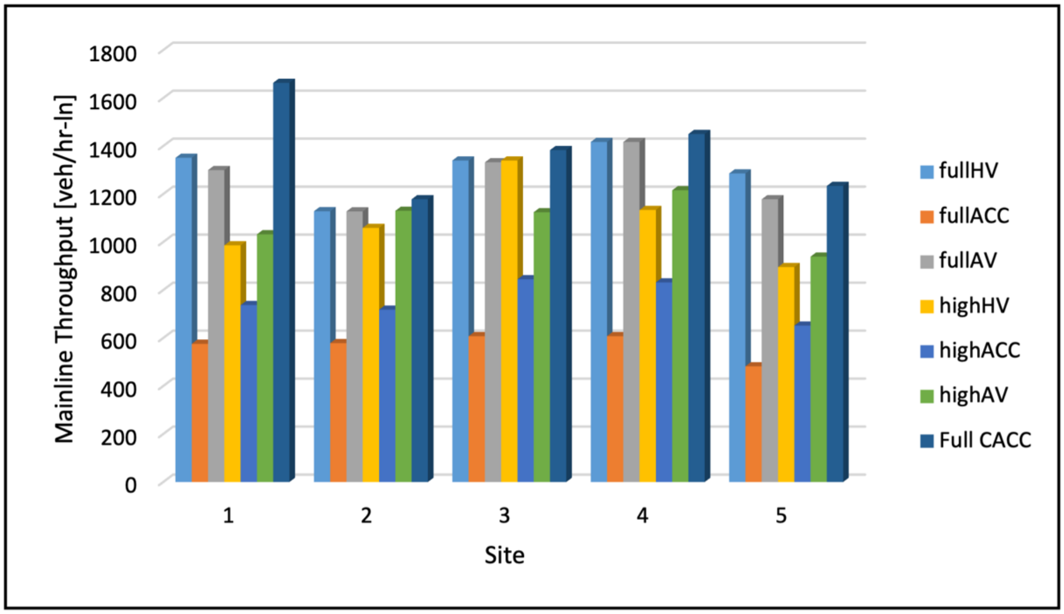


**Figure 3. Mainline throughput for each site and automation scenario.**

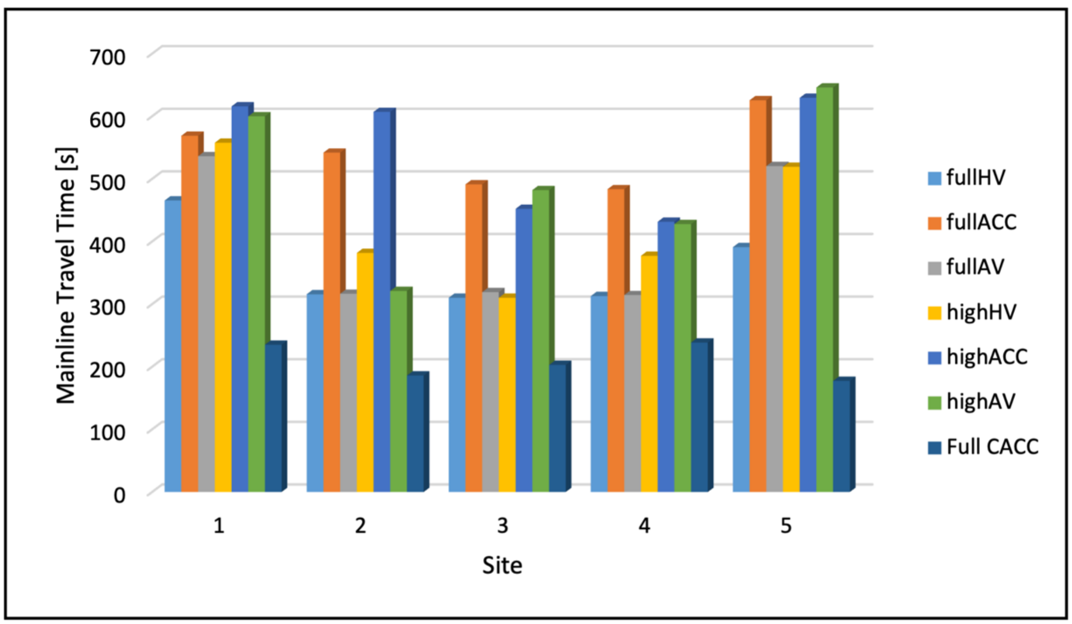


**Figure 4. Mainline travel time for each site and automation scenario.**

## 4.2 Ramp Queue Results

Figure 5 and Figure 6 showcase the findings regarding ramp queue lengths and wait times. The full HV and AV scenarios show significant discrepancies compared to the full commercial ACC scenarios which exhibit noticeably longer wait times and queue lengths. Within the mixed-autonomy scenarios, a general trend prevails, wherein the high HV and ACC scenarios exhibit comparable values, with an exception noted at Site 4 where the high ACC scenario displays notably lower queue lengths and wait times. At each site, the high AV scenario consistently registers the highest queue wait times and queue lengths. However, it is observed that the Full CACC scenario performs significantly better than all other automation scenarios. Since these results appear speculative, we set them aside and focus on comparing the outcomes among other automation scenarios.

Therefore, the overarching observation is that high or full HV and AV scenarios typically result in increased queue lengths and wait times compared to their high or full ACC counterparts. This observation aligns with expectations, given that ACC vehicles maintain larger following distances, which in turn leads to reduced mainline density levels and consequently faster meter release rates. Although these ramp queue conditions may appear favorable, the associated overly aggressive release rates contribute to the higher travel times and diminished throughput trends discussed earlier for ACC vehicles.

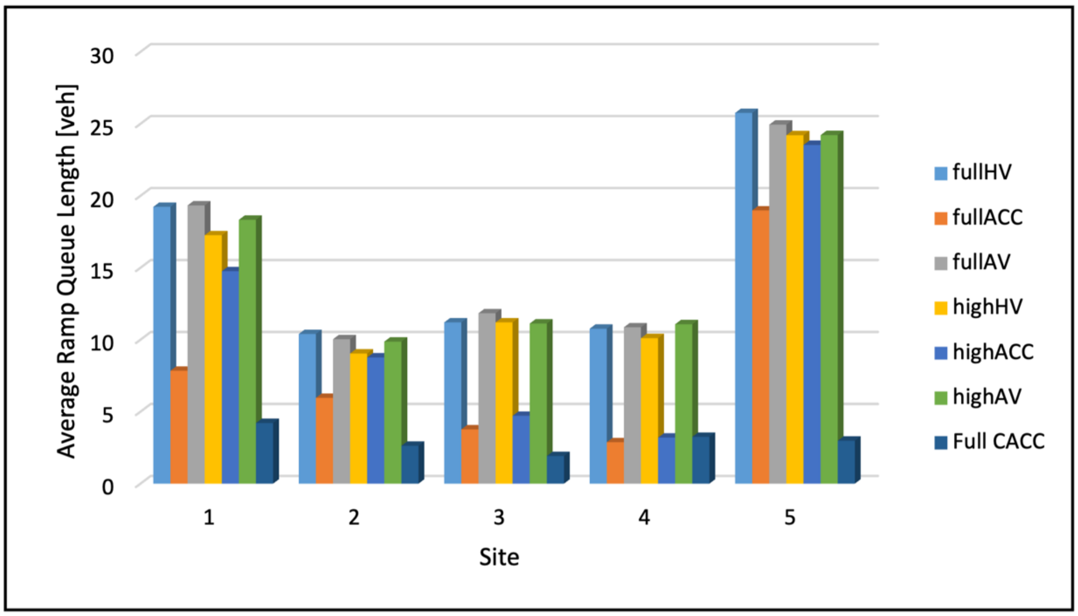


**Figure 5. Average ramp queue lengths for each site and automation scenario**

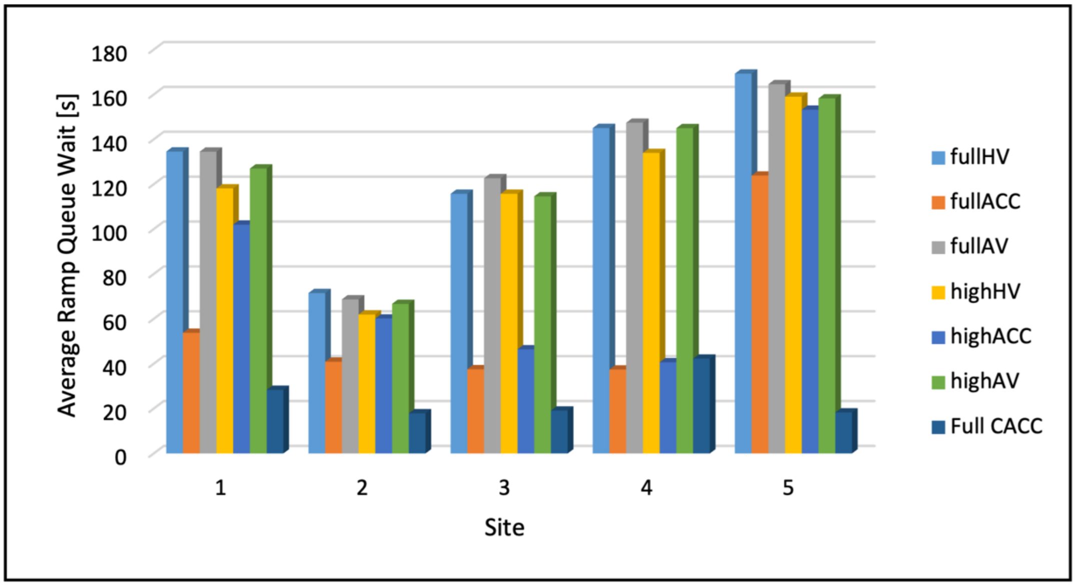


**Figure 6. Average ramp wait times for each site and automation scenario.**

## 4.3 Numerical results

This section presents the numerical results obtained in the simulations of MnDOT's Density Adaptive Metering Algorithm on the selected ramp-meter sites. Each of the following tables shows the results for one of the sites simulated under different automation scenarios. The best performance among all the scenarios is highlighted for each scenario.

As discussed earlier, the Full CACC scenario demonstrates significantly better performance than all other automation scenarios in all evaluation metrics. However, since these results appear speculative and require further validation, they are not directly compared with those from other scenarios. Instead, our primary focus remains on evaluating the relative performance of the HV, AV, and ACC scenarios to derive more reliable conclusions regarding automation impacts on ramp metering and traffic dynamics.

As it is bolded in Tables 8-12, the full HV scenarios show the least total travel time on all Sites and the highest on the mainline on all Sites except Site 2. In Site 2, the high HV scenario shows slightly higher throughput. The full AV scenario in Site 2 shows an equal throughput rate as the full HV scenario.

Table 8. Numerical results of site 1 under different scenarios.

| Scenarios | Full HV | Full ACC | Full AV | High HV | High ACC | High AV | Full CACC |
|---|---|---|---|---|---|---|---|
| **Total Travel Time [s]** | 464.36 | 588.56 | 234.82 | 504.65 | 446.85 | 403.08 | 235.15 |
| **Mainline Throughput [veh/hr-ln]** | 1343 | 561 | 1677 | 984 | 823 | 1400 | 1343 |
| **Ramp Avg Queue Length [veh]** | 19.23 | 7.84 | 19.33 | 17.26 | 14.76 | 18.33 | 4.21 |
| **Ramp Max Queue Length [veh]** | 29.00 | 21.00 | 29.00 | 27.00 | 27.00 | 28.00 | 7.00 |
| **Ramp Avg Queue Wait [sec]** | 131.03 | 114.84 | 22.61 | 80.05 | 76.97 | 37.35 | 28.33 |

**Table 9. Numerical results of site 2 under different scenarios.**

| Scenarios | Full HV | Full ACC | Full AV | High HV | High ACC | High AV | Full CACC |
|---|---|---|---|---|---|---|---|
| **Mainline Total Travel Time [s]** | 317.6 | 569.4 | 184.78 | 462.22 | 509.56 | 235.19 | 186.04 |
| **Mainline Throughput [veh/hr-ln]** | 1124 | 563 | 1177 | 941 | 776 | 986 | 1178 |
| **Ramp Avg Queue Length [veh]** | 10.40 | 5.96 | 10.03 | 9.04 | 8.77 | 9.87 | 2.63 |
| **Ramp Max Queue Length [veh]** | 19.00 | 11.00 | 19.00 | 16.00 | 17.00 | 19.00 | 4.00 |
| **Ramp Avg Queue Wait [sec]** | 30.06 | 55.64 | 22.53 | 36.43 | 32.33 | 35.9 | 17.90 |

**Table 10. Numerical results of site 3 under different scenarios.**

| Scenarios | Full HV | Full ACC | Full AV | High HV | High ACC | High AV | Full CACC |
|---|---|---|---|---|---|---|---|
| **Total Travel Time [s]** | 304.66 | 513.88 | 203.13 | 415.99 | 458.64 | 403.08 | 202.85 |
| **Mainline Throughput [veh/hr-ln]** | 893 | 348 | 923 | 698 | 555 | 916 | 1383 |
| **Ramp Avg Queue Length [veh]** | 11.20 | **3.77** | 11.83 | 11.20 | 4.71 | 11.12 | 1.92 |
| **Ramp Max Queue Length [veh]** | 19.00 | **6.00** | 20.00 | 19.00 | 11.00 | 19.00 | 3.00 |
| **Ramp Avg Queue Wait [sec]** | 29.96 | 147.24 | 23.16 | 68.42 | 83.05 | 37.35 | 19.12 |

**Table 11. Numerical results of site 4 under different scenarios.**

| Scenarios | Full HV | Full ACC | Full AV | High HV | High ACC | High AV | Full CACC |
|---|---|---|---|---|---|---|---|
| **Total Travel Time [s]** | **313.88** | **482.57** | **213.67** | **399.64** | **447.57** | **365.1** | **238.69** |
| **Mainline Throughput [veh/hr-ln]** | 1411 | 613 | 1459 | 1104 | 847 | 1375 | 1450 |
| **Ramp Avg Queue Length [veh]** | 10.76 | **2.88** | 10.86 | 10.11 | 3.20 | 11.07 | 3.25 |
| **Ramp Max Queue Length [veh]** | 16.00 | **6.00** | 16.00 | 16.00 | 7.00 | 17.00 | 5.00 |
| **Ramp Avg Queue Wait [sec]** | 38.58 | 33.83 | 27.36 | 46.45 | 42.2 | 35.82 | 42.25 |

Table 12.Numerical results of site 5 under different scenarios.

| Scenarios | Full HV | Full ACC | Full AV | High HV | High ACC | High AV | Full CACC |
|---|---|---|---|---|---|---|---|
| **Total Travel Time [s]** | 385.22 | 652.34 | 177.04 | 610.34 | 448.34 | 228.66 | 177.42 |
| **Mainline Throughput [veh/hr-ln]** | 1311 | 473 | 1550 | 834 | 737 | 1457 | 1233.66 |
| **Ramp Avg Queue Length [veh]** | 25.75 | **18.98** | 24.94 | 24.21 | 23.53 | 24.21 | 2.98 |
| **Ramp Max Queue Length [veh]** | 47.00 | **44.00** | 46.00 | 50.00 | 47.00 | 50.00 | 6 |
| **Ramp Avg Queue Wait [sec]** | 142.31 | 88.88 | 21.42 | 143.51 | 85.16 | 69.9 | 18.25 |

The findings regarding the ramp queue lengths and wait times show that the full ACC scenarios outperform all other scenarios in all Sites. However, the high ACC scenario in Site 4 shows an equal maximum wait time as the full ACC scenario. As explained earlier, these results align with expectations about ACC vehicles, as they maintain larger following distances. This, in turn, reduces mainline density levels and leads to faster meter release rates.

## 4.4 Level of service

In this section, we discuss the simulation results and calculation of the level of service (LOS) for various sites under different automation scenarios.

Table 13 outlines the criteria for determining the LOS of freeways. To determine the LOS for different scenarios, we utilized the average density of the mainline during the simulation. It's worth noting that the assumptions made regarding demand are uniform across all scenarios.

**Table 13. Level of Service criteria for freeways.**

| Level of Service | Density Range for Basic Freeway Section (pc/mi/ln) |
|---|---|
| A | $\geq 0 \leq 11$ |
| B | $> 11 \leq 18$ |
| C | $> 18 \leq 26$ |
| D | $> 26 \leq 35$ |
| E | $> 35 \leq 45$ |
| F | Demand Exceeds Capacity $> 45$ |

Tables 14 to 18 represent the comparison between different automation scenarios, detailing the LOS and mainline throughput. Across all sites, the Full ACC scenarios consistently produce lower density, which artificially improves the LOS, while reducing throughput. Conversely, the Full HV scenario showcases the poorest LOS across all sites except Site 2. These results are in line with expected outcomes for ACC vehicles as they tend to maintain greater following distances, which reduces overall traffic density at the cost of lower overall throughput.

While the Full HV scenario performs poorly in terms of LOS, both the Full HV and High HV scenarios exhibit the highest mainline throughput. This indicates that despite their impact on overall traffic density, HV scenarios showcase a notable capacity for throughput enhancement. The High AV and Full AV scenarios fall somewhere in between. They have slightly lower throughput compared to HV scenarios but also show higher average mainline density.

**Table 14. Average density of Level of Service for site 1 under different scenarios.**

| Scenarios | Full HV | Full ACC | Full AV | High HV | High ACC | High AV | Full CACC |
|---|---|---|---|---|---|---|---|
| **Mainline Throughput [veh/hr-ln]** | **1350.67** | 575.67 | 1299.67 | 986.00 | 737.00 | 1031.67 | 1663.3 |
| **Average Density of the Mainline [veh/mi/ln]** | 18.83 | **9.22** | 20.13 | 15.46 | 13.28 | 18.55 | 38.18 |
| **Level of Service** | C | A | C | B | B | C | E |

**Table 15. Average density of Level of Service for site 2 under different scenarios.**

| Scenarios | Full HV | Full ACC | Full AV | High HV | High ACC | High AV | Full CACC |
|---|---|---|---|---|---|---|---|
| **Mainline Throughput [veh/hr-ln]** | 1128.00 | 578.67 | 1127.33 | 1058.67 | 718.00 | **1129.67** | 1178 |
| **Average Density of the Mainline [veh/mi/ln]** | 10.84 | **9.27** | 10.98 | 10.87 | 11.91 | 11.30 | 20.72 |
| **Level of Service** | A | A | A | A | B | B | C |

**Table 16. Average density of Level of Service for site 3 under different scenarios.**

| Scenarios | Full HV | Full ACC | Full AV | High HV | High ACC | High AV | Full CACC |
|---|---|---|---|---|---|---|---|
| **Mainline Throughput [veh/hr-ln]** | **1339.50** | 607.50 | 1332.00 | **1339.50** | 844.50 | 1124.00 | 1383 |
| **Average Density of the Mainline [veh/mi/ln]** | 18.62 | **12.41** | 19.45 | 17.24 | 14.81 | 24.19 | 26.80 |
| **Level of Service** | C | B | C | B | B | C | D |

**Table 17. Average density of Level of Service for site 4 under different scenarios.**

| Scenarios | Full HV | Full ACC | Full AV | High HV | High ACC | High AV | Full CACC |
|---|---|---|---|---|---|---|---|
| **Mainline Throughput [veh/hr-ln]** | **1416.67** | 607.67 | **1416.67** | 1133.33 | 831.67 | 1215.33 | 1450 |
| **Average Density of the Mainline [veh/mi/ln]** | 13.02 | **7.44** | 13.33 | 11.44 | 8.38 | 15.01 | 30.21 |
| **Level of Service** | C | A | C | B | B | C | D |

**Table 18. Average density of Level of Service for site 5 under different scenarios.**

| Scenarios | Full HV | Full ACC | Full AV | High HV | High ACC | High AV | Full CACC |
|---|---|---|---|---|---|---|---|
| **Mainline Throughput [veh/hr-ln]** | **1285.50** | 482.00 | 1178.00 | 895.50 | 651.50 | 939.00 | 1233.66 |
| **Average Density of the Mainline [veh/mi/ln]** | 27.69 | **18.28** | 31.01 | 23.34 | 22.08 | 28.25 | 27.23 |
| **Level of Service** | D | C | D | C | C | D | D |

## 4.5 Summary of impacts results

The average percent change of each automation scenario compared to the Full HV (baseline) scenario is presented in Table 19.

**Table 19: Average percent change in performance metrics for each automation scenario across all five sites.**

| Scenario | ML Throughput | ML travel time | Avg Ramp wait time |
|---|---:|---:|---:|
| Full ACC | -58.4 | 61.1 | 134.3 |
| Full AV | 9.7 | -40.6 | -44.5 |
| High HV | -24.1 | 35.5 | 43.4 |
| High ACC | -38.2 | 36.1 | 48.3 |
| High AV | 9.0 | 0.2 | -10.1 |
| Full CACC | 10.8 | -40.7 | -79.5 |

# Chapter 5: Proposed adjustments to ramp metering for mixed autonomy traffic

The findings presented earlier indicate that varying degrees of automation at different levels of traffic flow significantly affect both traffic flow and level of service (LOS). Specifically, we found that the first generation of automation, which includes driver assist features like ACC, generally decreases maximum throughput and increases the spacing between vehicles. While this may improve LOS, it does so artificially, as the overall throughput is reduced. As automation technology becomes more advanced, the next generation of automated vehicles is expected to drive safely and efficiently with minimal inter-vehicle spacing.

Given the exceptional performance of the Full CACC scenario across all evaluation metrics, no further adjustments were considered necessary. This scenario inherently enhances all critical characteristics of merge sections, optimizing traffic flow, reducing congestion, and improving overall system efficiency without requiring additional modifications.

We propose two adjustment scenarios to MnDOT's Density Adaptive Metering Algorithm to enhance the overall traffic flow by increasing throughput and reducing travel time at ramp metering in the first six automation scenarios. The first adjustment mainly focuses on decreasing the wait time for vehicles entering the highway from the ramp. However, this scenario does not consistently improve throughput and travel time on the highway's mainline. The second adjustment for some of the ramp meter sites results in increased wait times on the ramp, but it improves throughput and reduces wait times on the mainline. In the following sections, we will explore the proposed adjustments in detail.

## 5.1 Adjustment 1: Change of critical density and jam density:

In a fundamental diagram, critical density ($\rho_{cr}$) is the point where traffic reaches its maximum sustainable flow rate on the roadway and defines the cutoff between free-flow and congested regimes. Jam density ($\rho_j$) refers to the point at which traffic density reaches its maximum value during congestion. At $\rho_j$, the traffic flow rate approaches zero, and vehicles reach a complete standstill. Diverse macroscopic fundamental diagrams, with varying $\rho_j$ and $\rho_{cr}$, may lead to distinct designs in ramp metering control algorithms. As for mixed-autonomy traffic, $\rho_j$ and $\rho_{cr}$ vary across different market penetration rates due to the differences in fundamental diagrams. We present the updated values for $\rho_j$ and $\rho_{cr}$ in the following table. Specifically, $\rho_j$ and $\rho_{cr}$ are decreased as the ACC MPR is increased, whereas $\rho_j$ and $\rho_{cr}$ are increased as the AV MPR is increased. The results are aligned with the findings of Shang and Stern (2021), which suggest the presence of an ACC vehicle might reduce the capacity due to a shrink fundamental diagram, and an AV may increase the capacity with an expanded fundamental diagram as the MPR increases.

We utilized the IDM parameter values presented in Table 4 to estimate the mixed-autonomy fundamental diagrams. Table 20 represents the calculated critical density, jam density, and capacity of the mixed autonomy scenarios based on Shang et al. (2023). Specifically, jam density and critical density are decreased as the ACC MPR is increased, whereas jam density and critical density are increased as the AV MPR is increased. The results are aligned with the findings of Shang and Stern (2021), which suggest the presence of an ACC vehicle might reduce the capacity due to a shrink fundamental diagram, and an AV may increase the capacity with an expanded fundamental diagram as the MPR increases. The triangular fundamental diagrams of the mixed autonomy scenarios are presented in Figure 7. The first adjustment to the MnDOT's Density Adaptive Metering Algorithm is to consider the updated values for the critical density and desired density as presented in Table 20.

**Table 20. Adjusted metering parameters for each mixed autonomy scenario**

| Scenario | Critical Density (veh/mi) | Jam Density (veh/mi) | Capacity (veh/hr) |
|---|---|---|---|
| **Full HV** | 51.67 | 192.58 | 1909.50 |
| **Full ACC** | 22.88 | 142.42 | 1373.10 |
| **Full AV** | 72.74 | 214.57 | 4364.50 |
| **High HV** | 41.53 | 173.63 | 1653.80 |
| **High ACC** | 33.91 | 160.13 | 1540.30 |
| **High AV** | 52.66 | 190.67 | 2436.10 |

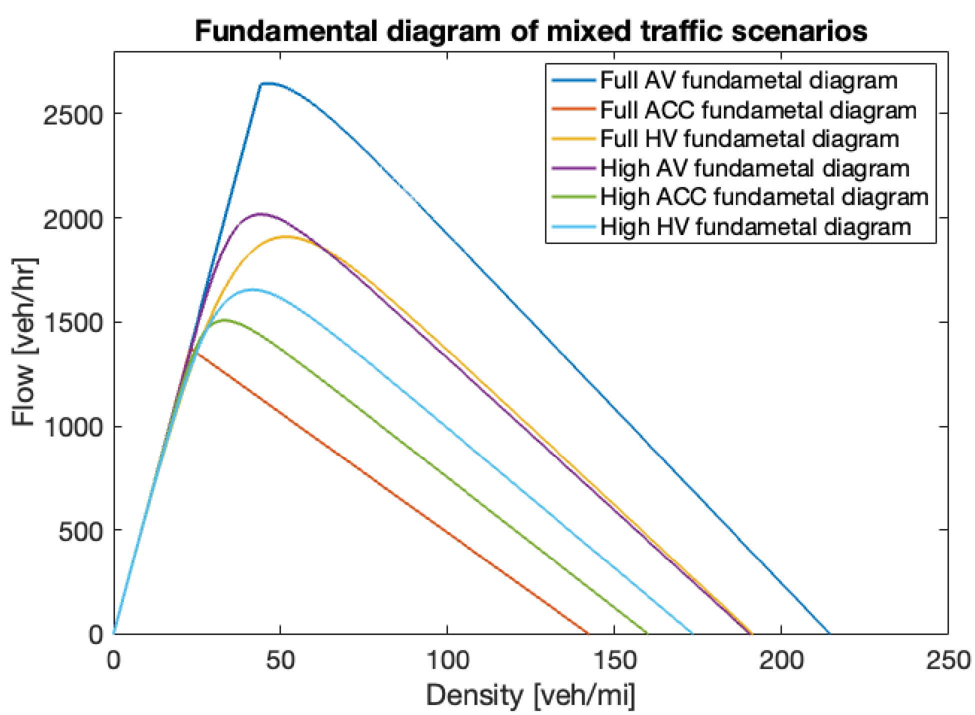


**Figure 7. Fundamental diagrams of mixed-autonomy traffic flow.**

## 5.2 Adjustment 2: Change of parameters for the meter activation and phases

In the MnDOT's Density Adaptive Metering Algorithm, two terms are used as the criteria for changing the phase meters, Low density and Desired density. The low density is the criterion that the phase changes between the flushing phase and the activated phase, and the desired density is the criterion to activate the ramp meter. The low density is defined as 75% of critical density and the desired density is defined as 90% of critical density. To increase the throughput and decrease the travel time on the highway mainline, we extend the time that the flow rate of vehicles on the mainline is high. Now, we delve deeper into the proposed adjustments to the low and desired densities.

### 5.2.1 Low Density adjustment

Based on the algorithm, the low density is the density threshold for determining whether metering should continue (maximum of 75% of critical density and 27.75 vehicles per lane-mile). The proposed adjustment is to change the 75% multiplier to the ratio of:

$$\frac{adjusted\ capacity}{default\ capacity} \times 75\%.$$

This results in maintaining the ramp meter in the flushing state longer for vehicles with higher determined capacity in the FD. Table 21 represents the calculated parameters for each mixed autonomy traffic scenario by using the values in Table 20. For a full human-driven environment, we have the default value of 75%.

**Table 21. Adjustments to the parameter value in the low-density equation.**

| Scenario | Parameter value for desired density |
|---|---|
| Full HV | 75% |
| Full ACC | 54% |
| Full AV | 171% |
| High HV | 65% |
| High ACC | 60% |
| High AV | 96% |

### 5.2.2 Desired Density adjustment

Based on the algorithm, the desired density is the density threshold for determining whether metering is necessary (maximum of 90% of critical density and  33.3 vehicles per lane-mile). The proposed adjustment is to change the 90% multiplier in desired density to the ratio of:

$$\frac{adjusted\ jam\ density}{default\ jam\ density} \times 90\%.$$

This results in turning the meter on at a higher rate of density (when we have more traffic volume on the mainline).  Table 22 represents the calculated parameters for each mixed autonomy traffic scenario by using the values in Table 20. For a full human-driven environment, we have the default value of 90%.

**Table 22. Adjustments to the parameter value in the desired density equation.**

| Scenario | Parameter value for desired density |
|---|---|
| Full HV | 90% |
| Full ACC | 65% |
| Full AV | 206% |
| High HV | 78% |
| High ACC | 73% |
| High AV | 115% |

## 5.3 Results of the simulation of proposed adjustments and discussion

Now, we present and discuss simulation results for both adjustment scenarios and compare them with the default conditions.

### 5.3.1 Visualization of Results

The findings regarding mainline throughput are visually presented in Figures 8-12. It is observed in the figures that the throughput value is improved for all the automation scenarios in the second adjustment. However, we can observe that in some of the simulated scenarios, the default scenarios have a higher rate of throughput than the first adjustment scenario. The reason is that the first adjustment is aimed at decreasing the wait time on the traffic flow of the ramp rather than improving the traffic flow on the mainline. In most scenarios involving fully autonomous vehicles (Full AVs), the ramp meter is not activated. This is mainly due to the precise following behavior of AVs in traffic, which helps prevent congestion from occurring. Therefore, the ramp meter is not needed for improving the traffic flow.

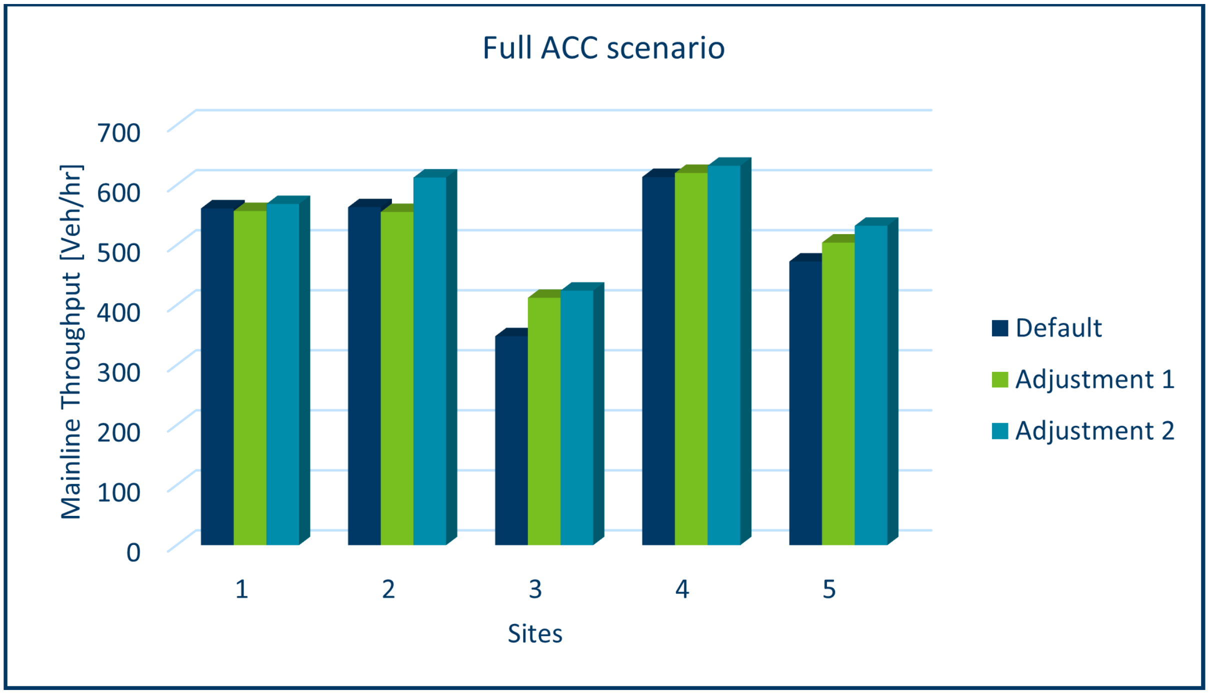


**Figure 8. Mainline throughput comparison between the default scenario and the proposed adjustments for a Full ACC traffic.**

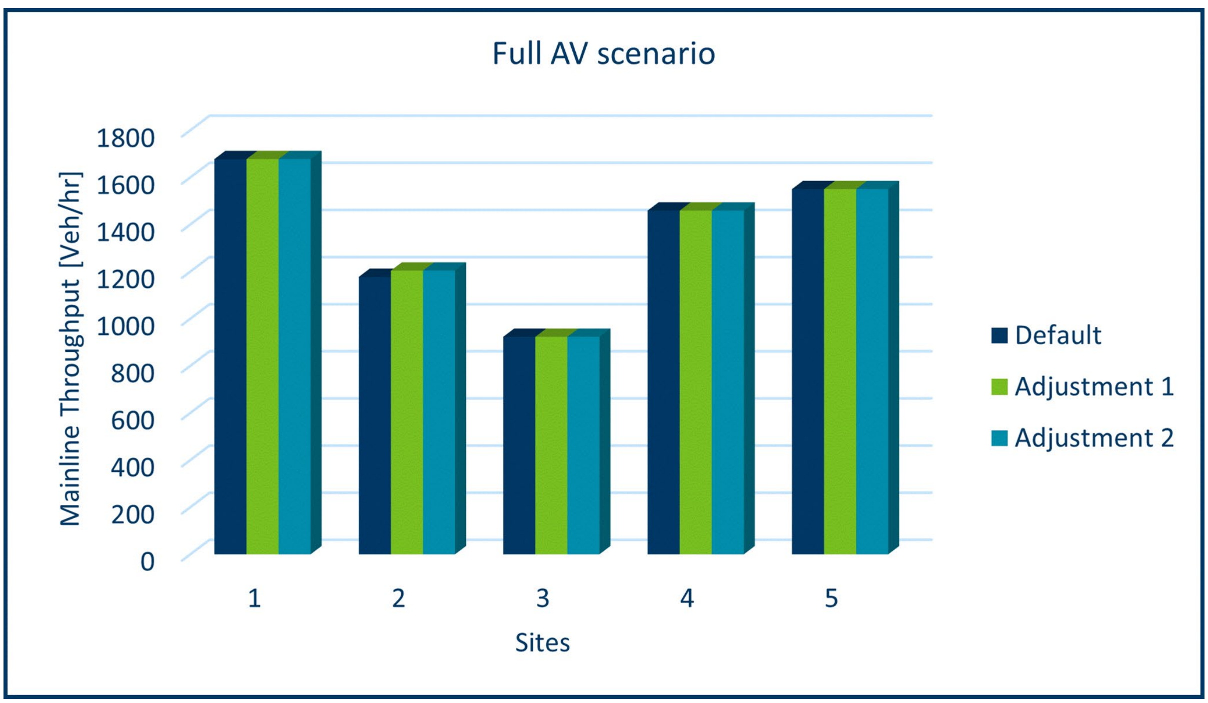


**Figure 9. Mainline throughput comparison between the default scenario and the proposed adjustments for a Full AV traffic.**

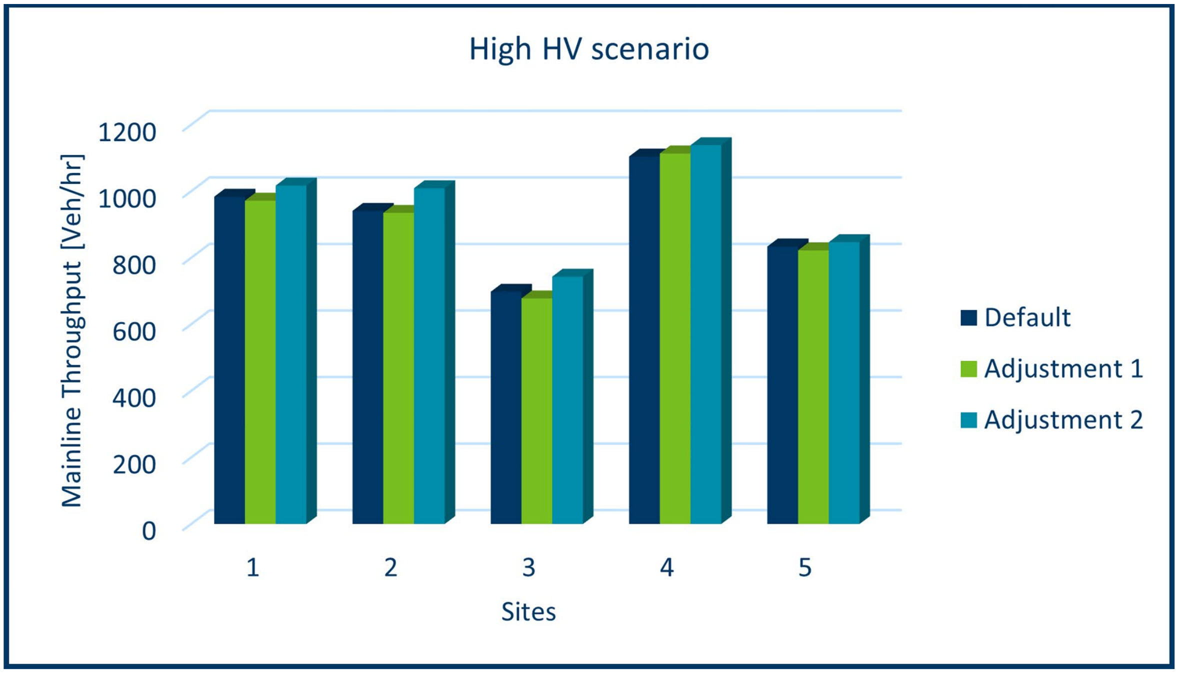


**Figure 10. Mainline throughput comparison between the default scenario and the proposed adjustments for a High HV traffic.**

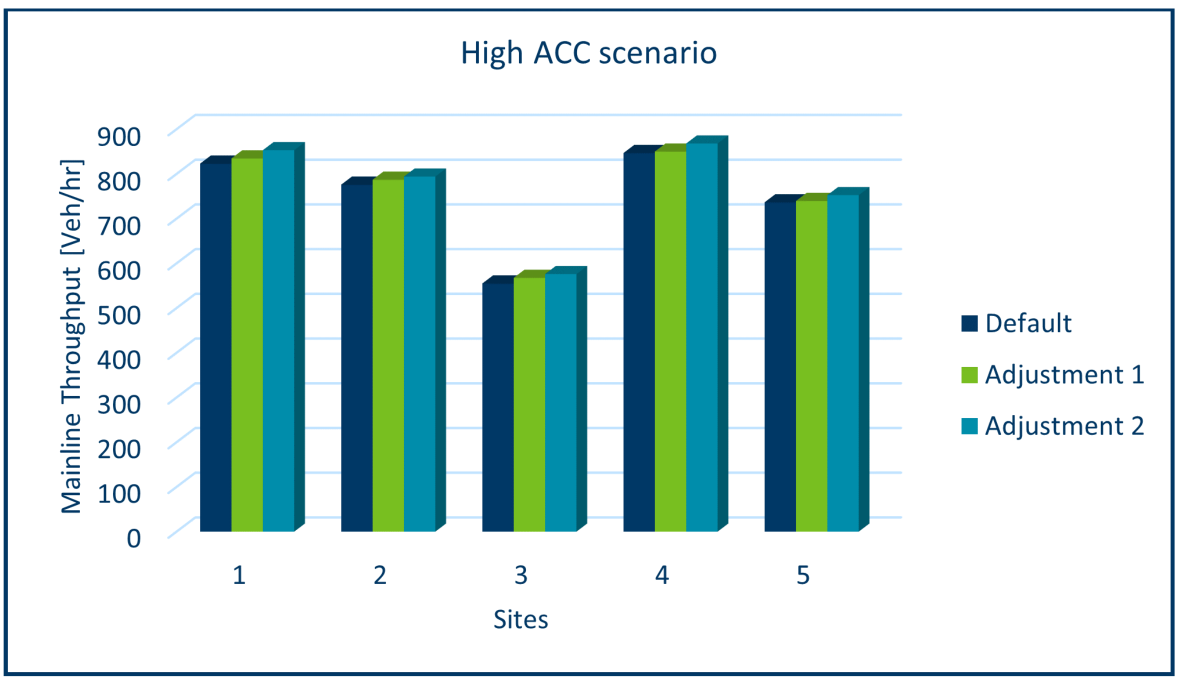


**Figure 11. Mainline throughput comparison between the default scenario and the proposed adjustments for a High ACC traffic.**

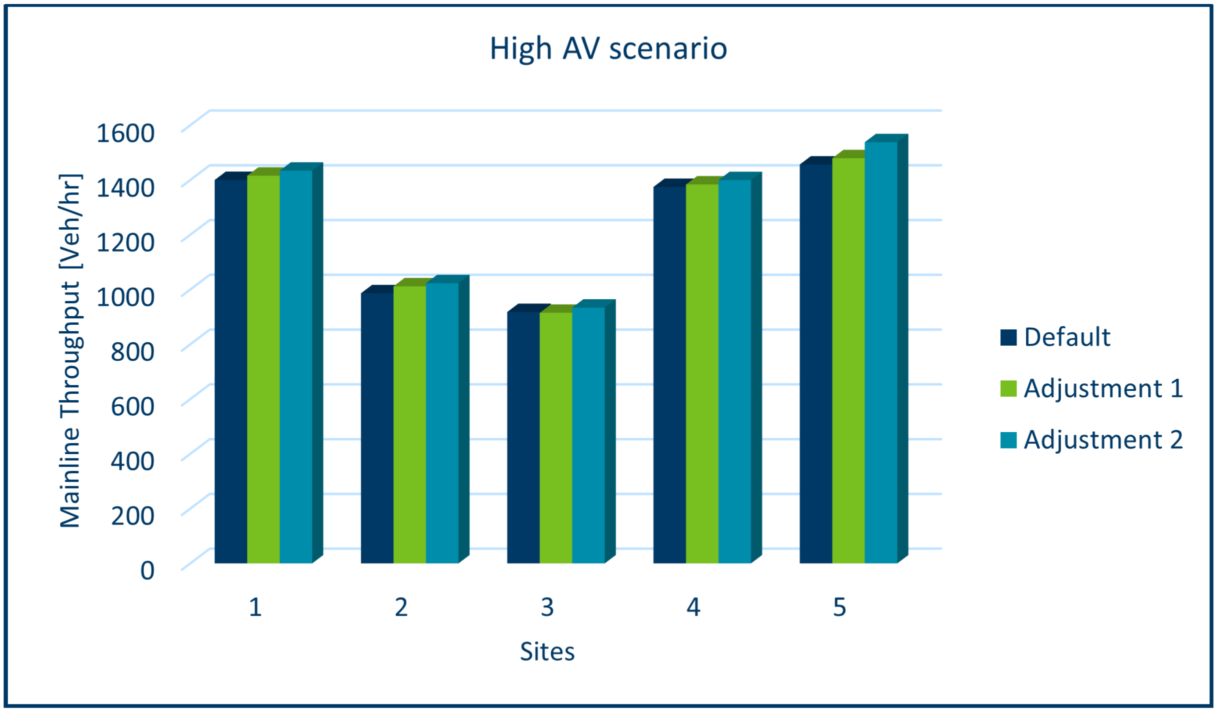


**Figure 12. Mainline throughput comparison between the default scenario and the proposed adjustments for a High AV traffic.**

Figures 13-17 represent the mainline travel time for different automation scenarios. The results are in coordination with the throughput results as the second adjustment improves the mainline travel time for all the scenarios compared to the default scenarios.

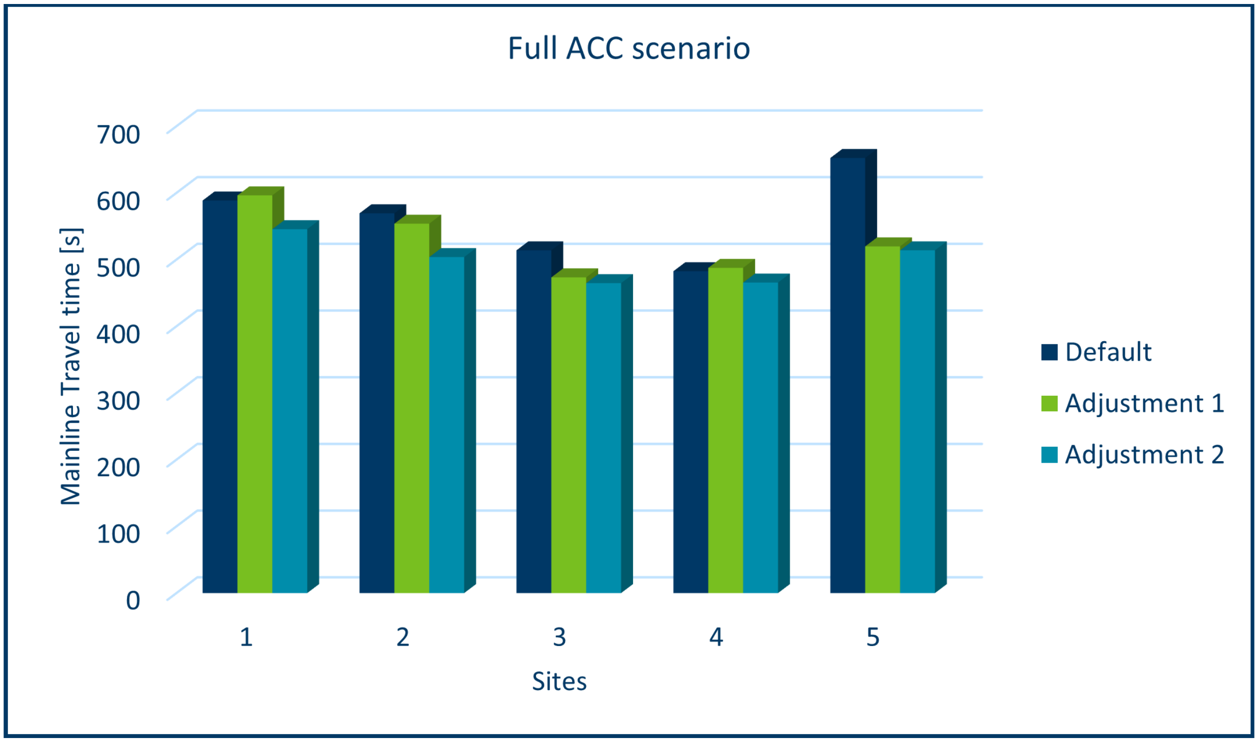


**Figure 13. Mainline travel time comparison between the default scenario and the proposed adjustments for a Full ACC traffic.**

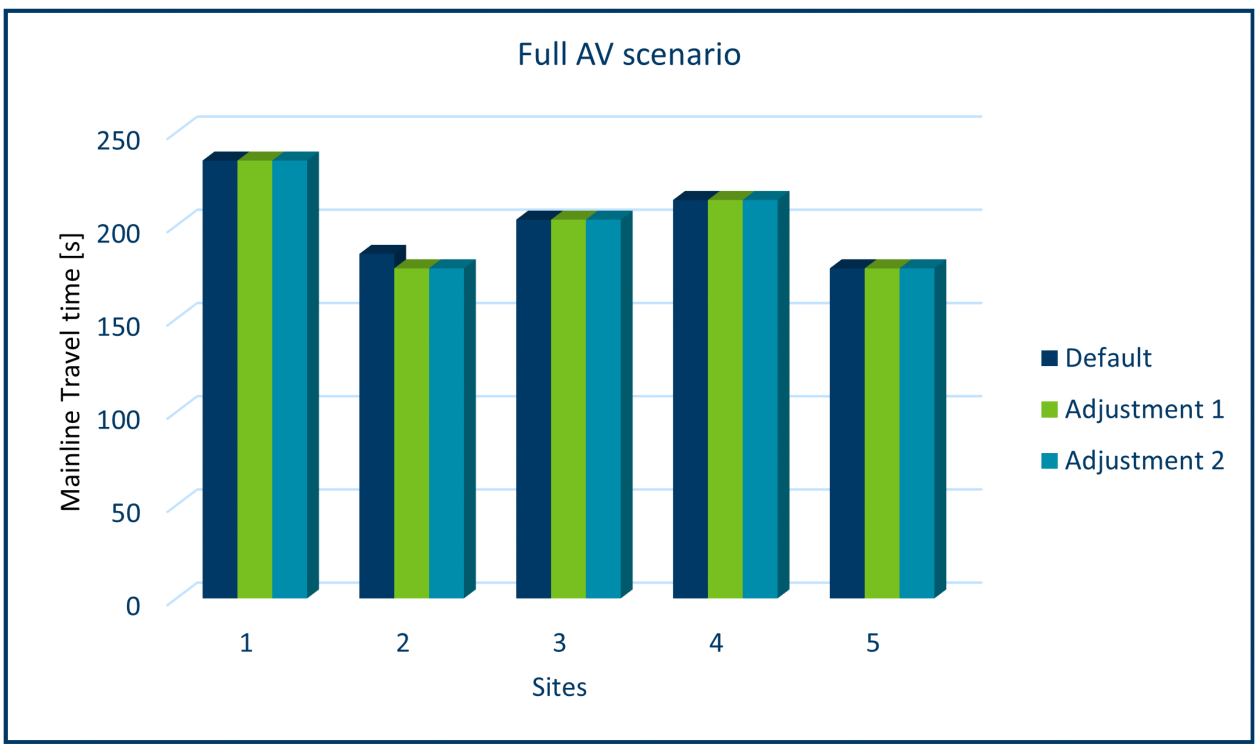


**Figure 14. Mainline travel time comparison between the default scenario and the proposed adjustments for a Full AV traffic.**

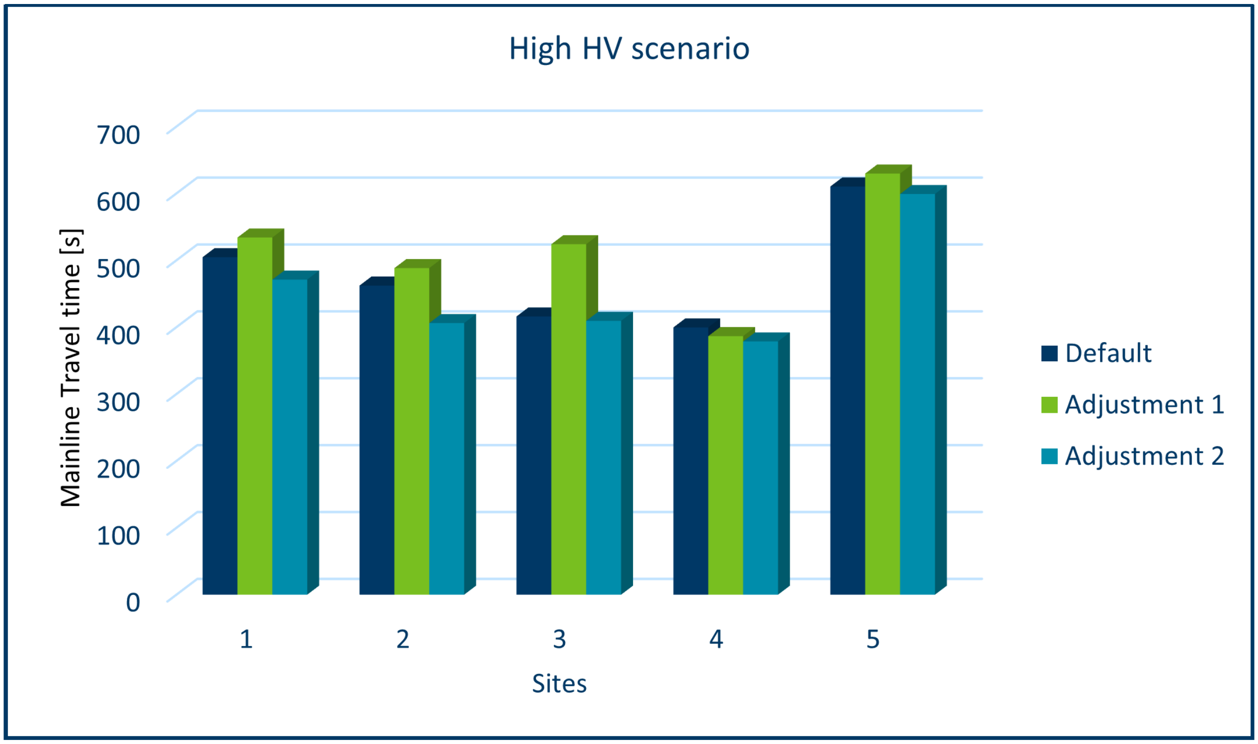


**Figure 15. Mainline travel time comparison between the default scenario and the proposed adjustments for a High HV traffic.**

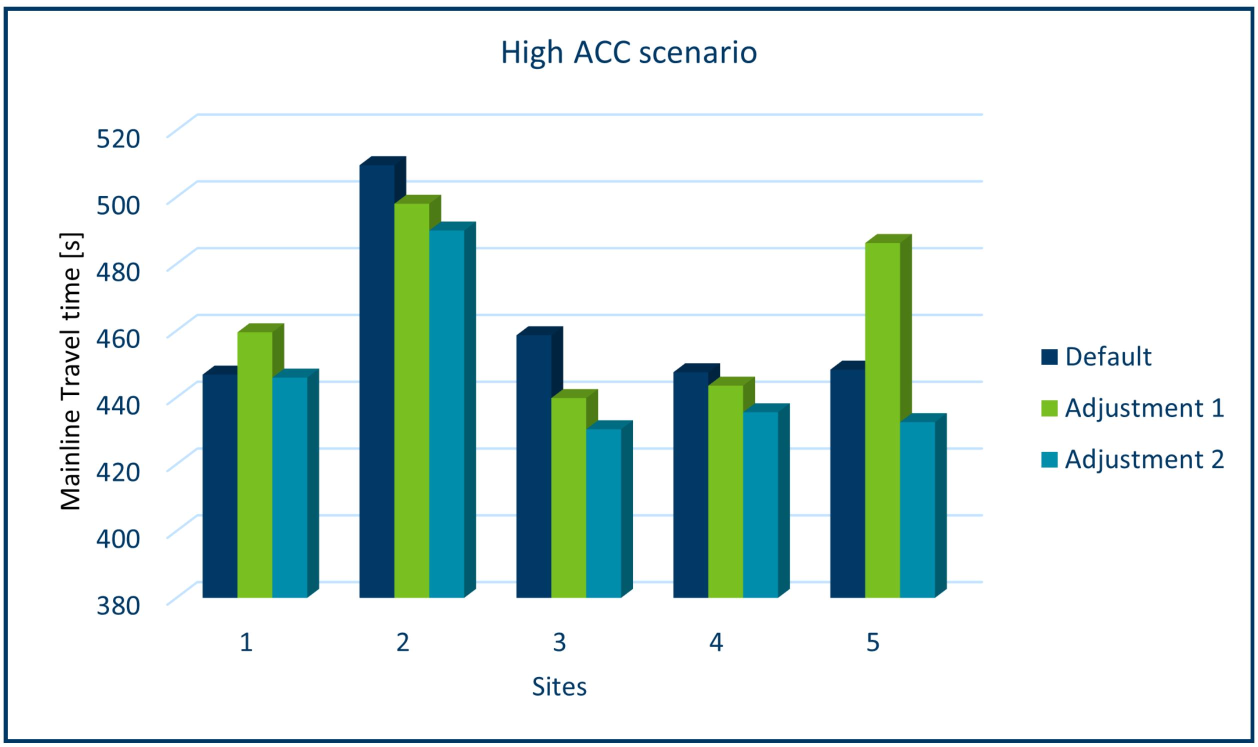


**Figure 16. Mainline travel time comparison between the default scenario and the proposed adjustments for a High ACC traffic.**

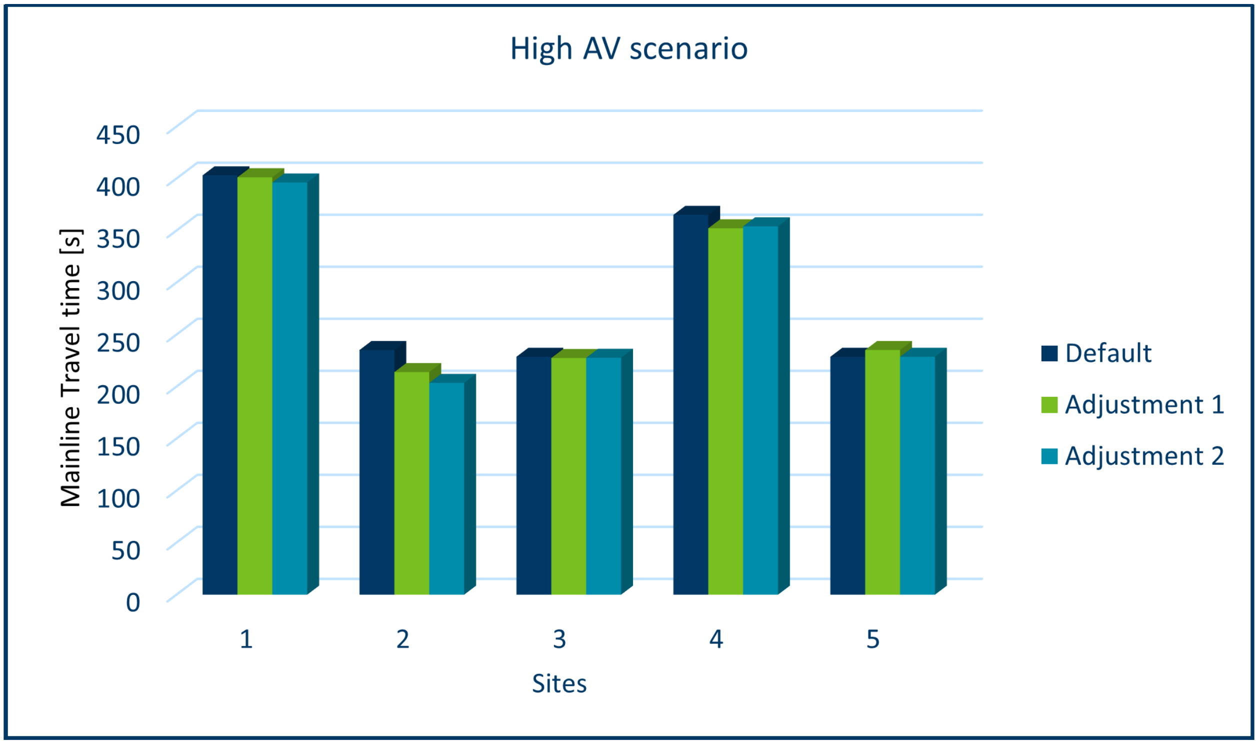


**Figure 17. Mainline travel time comparison between the default scenario and the proposed adjustments for a High AV traffic.**

The wait time on the ramp for the simulated mixed autonomy traffic scenarios is shown in Figures 18-22. Overall, the wait time on the ramp is decreased after the first adjustment. However, the second adjustment sometimes increases the ramp wait time compared to the default scenarios.

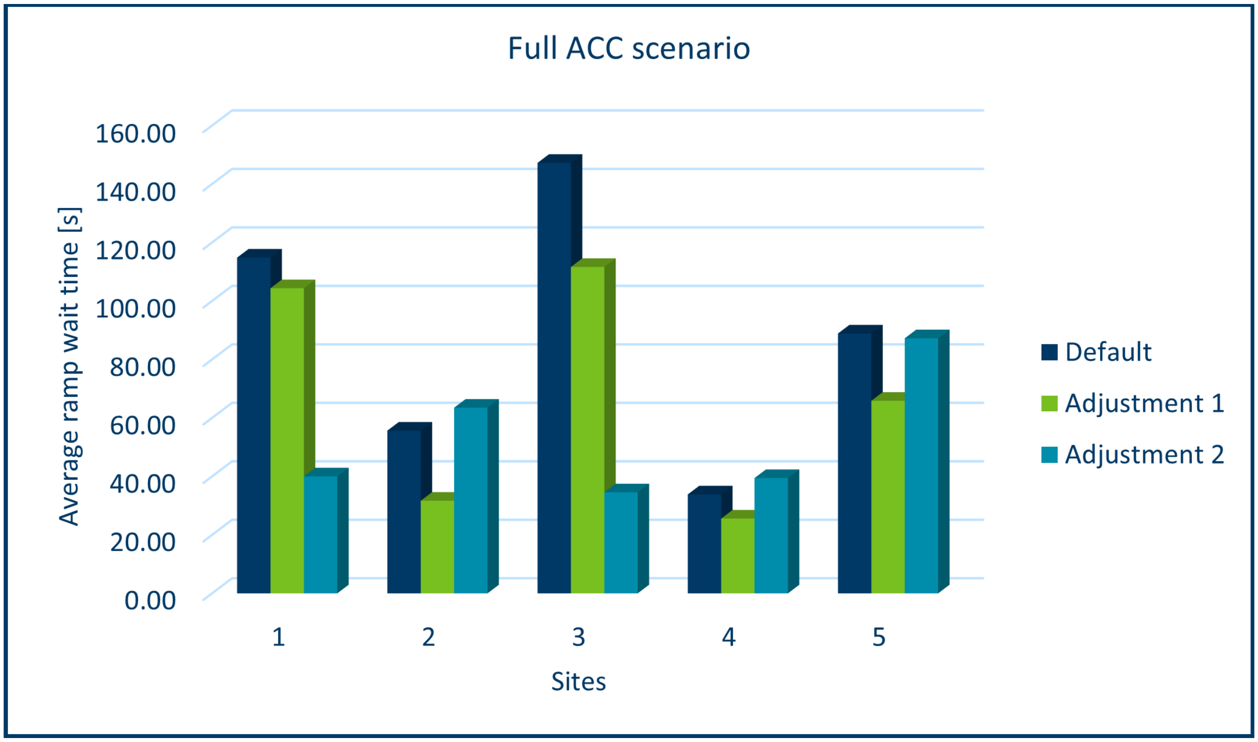


**Figure 18. Average ramp wait time comparison between the default scenario and the proposed adjustments for a Full ACC traffic.**

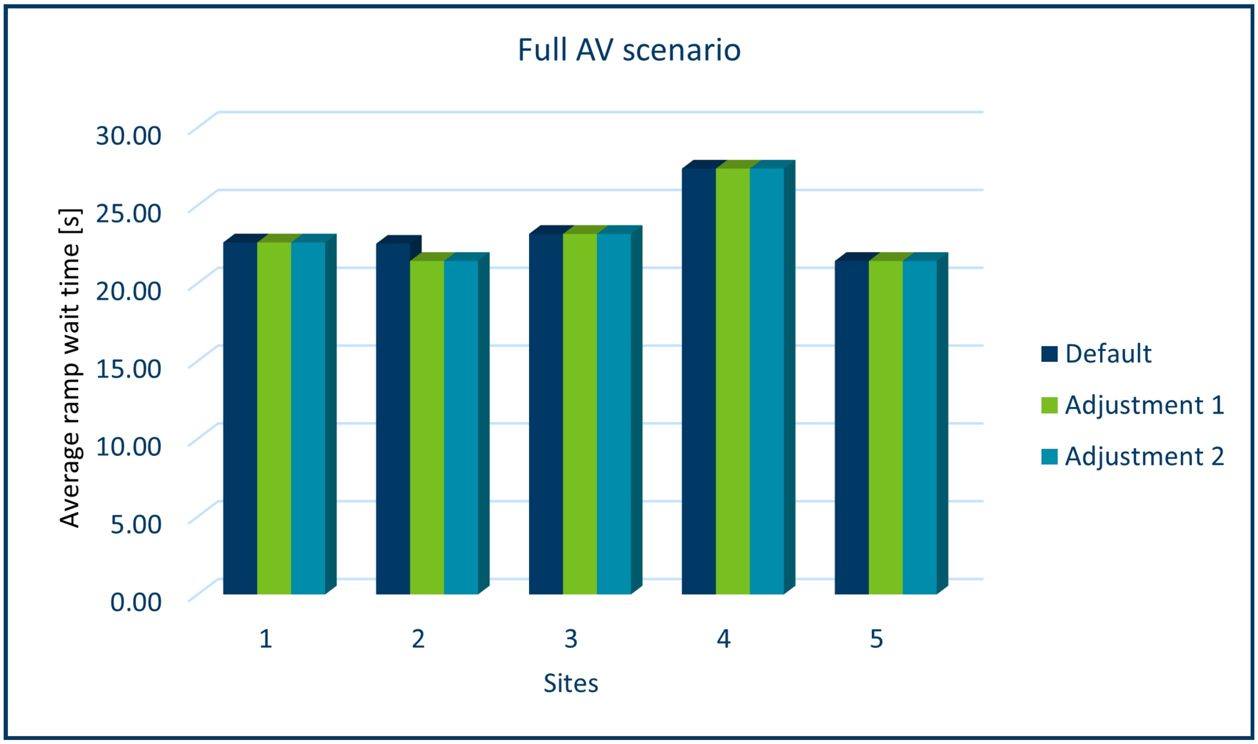


**Figure 19. Average ramp wait time comparison between the default scenario and the proposed adjustments for a Full AV traffic.**

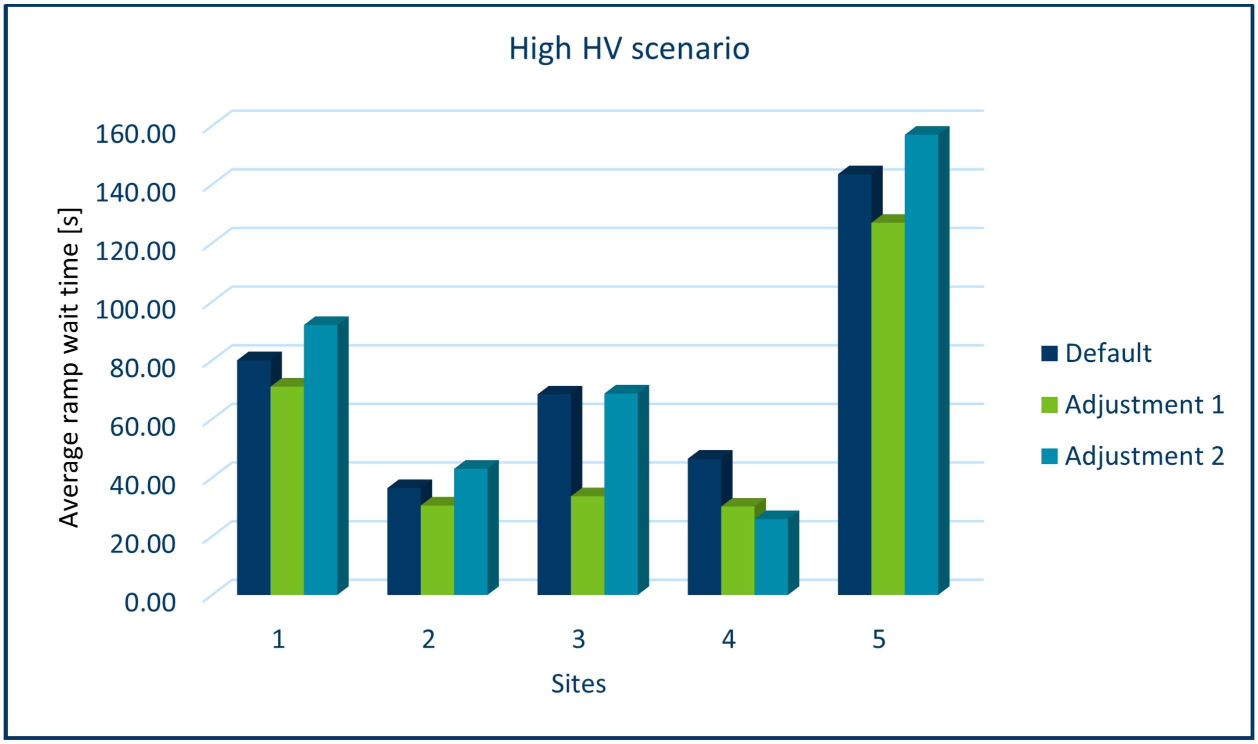


**Figure 20. Average ramp wait time comparison between the default scenario and the proposed adjustments for a High HV traffic.**

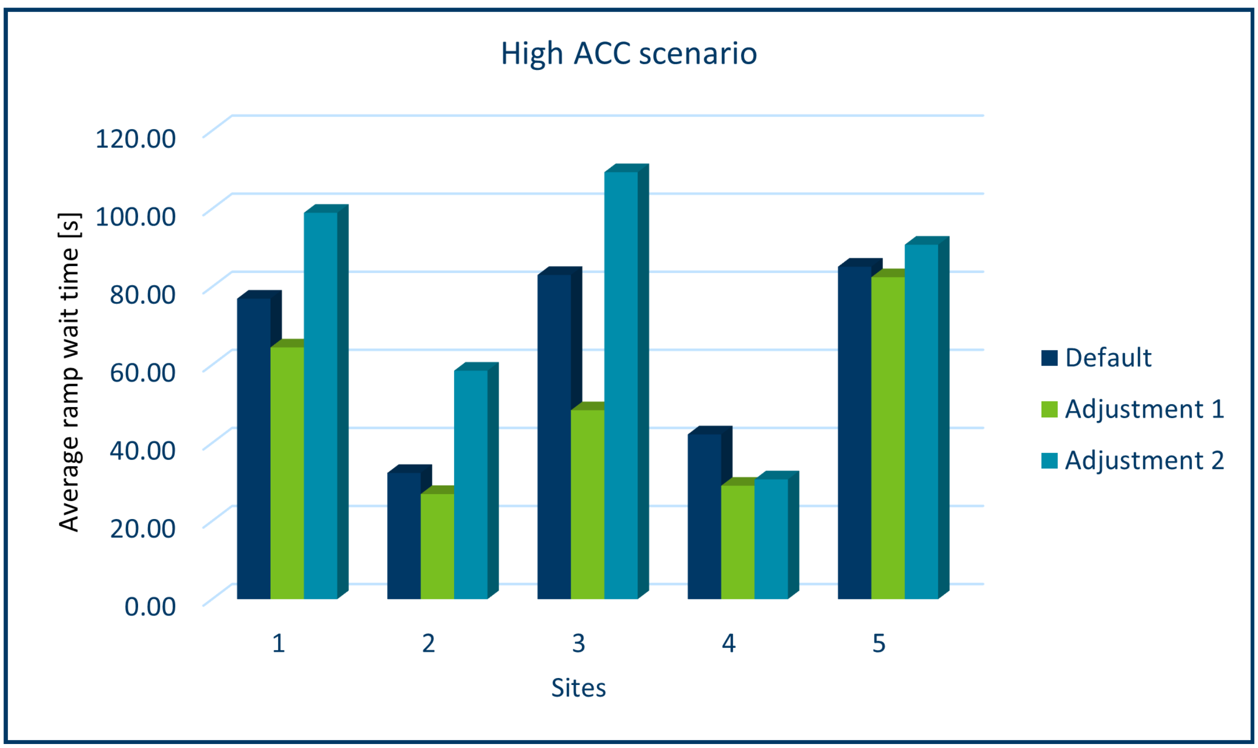


**Figure 21. Average ramp wait time comparison between the default scenario and the proposed adjustments for a High ACC traffic.**

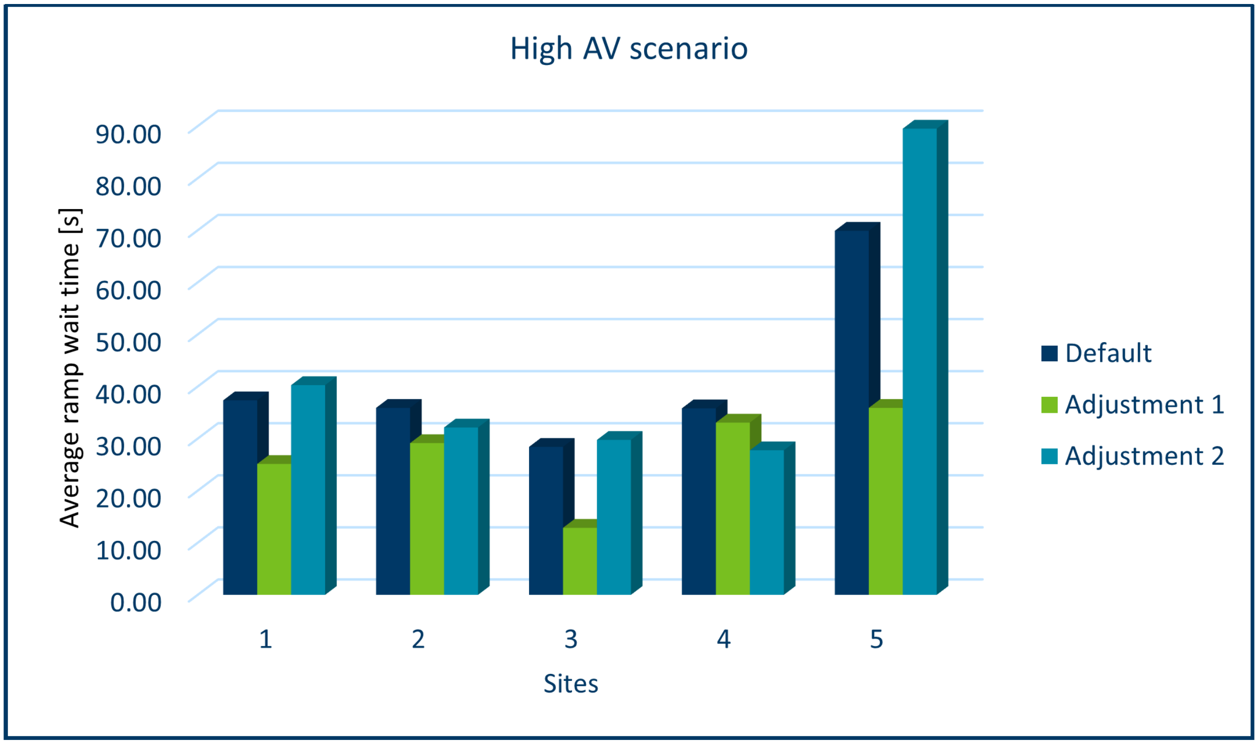


**Figure 22. Average ramp wait time comparison between the default scenario and the proposed adjustments for a High AV traffic.**

### 5.3.3 Numerical results

Here we present the numerical results obtained in the simulations. The discussion of these results is presented earlier. Each of the following tables shows the results for one of the Sites simulated under different scenarios. The best performance among all the scenarios is highlighted for each scenario.

**Table 23. Numerical results of the simulated scenarios for site 1.**

| Site 1 | Default | | | Adjustment 1 | | | Adjustment2 | | |
|---|---|---|---|---|---|---|---|---|---|
| | ML Through put | ML travel time | Avg R wait time | ML Through put | ML travel time | Avg R wait time | ML Through put | ML travel time | Avg R wait time |
| Full HV | 1343 | 464.36 | 131.03 | 1343 | 464.36 | 131.03 | 1343 | 464.36 | 131.03 |
| Full ACC | 561 | 588.56 | 114.84 | 557 | 596.32 | 104.36 | **568** | **545.6** | **39.99** |
| Full AV | 1677 | 234.82 | 22.61 | 1677 | 234.82 | 22.61 | 1677 | 234.82 | 22.61 |
| High HV | 984 | 504.65 | 80.05 | 972 | 534.05 | **71.03** | **1017** | **471.14** | 92.08 |
| High ACC | 823 | 446.85 | 76.97 | 835 | 459.53 | **64.49** | **853** | **445.96** | 98.97 |
| High AV | 1400 | 403.08 | 37.35 | 1416 | 401.22 | **25.13** | **1434** | **396.21** | 40.27 |

**Table 24. Numerical results of the simulated scenarios for site 2.**

| Site 2 | Default | | | Adjustment 1 | | | Adjustment2 | | |
|---|---|---|---|---|---|---|---|---|---|
| | **ML Through put** | **ML travel time** | **Avg R wait time** | **ML Through put** | **ML travel time** | **Avg R wait time** | **ML Through put** | **ML travel time** | **Avg R wait time** |
| Full HV | 1124 | 317.60 | 30.06 | 1124 | 317.60 | 30.06 | 1124 | 317.60 | 30.06 |
| Full ACC | 563 | 569.4 | 55.64 | 555 | 553.86 | **31.67** | **612** | **503.76** | 63.48 |
| Full AV | 1177 | 184.78 | 22.53 | 1204 | 177.04 | 21.42 | 1204 | 177.04 | 21.42 |
| High HV | 941 | 462.22 | 36.43 | 935 | 488.32 | **30.52** | **1009** | **406.14** | 43.01 |
| High ACC | 776 | 509.56 | 32.33 | 787 | 498.02 | **26.93** | **794** | **490.00** | 58.52 |
| High AV | 986 | 235.19 | 35.90 | 1012 | 213.97 | **29.14** | **1023** | **203.56** | 32.14 |

**Table 25. Numerical results of the simulated scenarios for site 3.**

| Site 3 | Default | | | Adjustment 1 | | | Adjustment2 | | |
|---|---|---|---|---|---|---|---|---|---|
| | **ML Through put** | **ML travel time** | **Avg R wait time** | **ML Through put** | **ML travel time** | **Avg R wait time** | **ML Through put** | **ML travel time** | **Avg R wait time** |
| Full HV | 893 | 304.66 | 29.96 | 893 | 304.66 | 29.96 | 893 | 304.66 | 29.96 |
| Full ACC | 348 | 513.88 | 147.24 | 412 | 473.33 | 111.64 | **424** | **464.66** | **34.56** |
| Full AV | 923 | 203.13 | 23.16 | 923 | 203.13 | 23.16 | 923 | 203.13 | 23.16 |
| High HV | 698 | 415.99 | 68.42 | 678 | 524.05 | **33.66** | **743** | **409.45** | 68.68 |
| High ACC | 555 | 458.64 | 83.05 | 568 | 439.83 | **48.39** | **576** | **430.48** | 109.36 |
| High AV | 1400 | 403.08 | 37.35 | 1416 | 401.22 | **25.13** | **1434** | **396.21** | 40.27 |

**Table 26. Numerical results of the simulated scenarios for site 4.**

| Site 4 | Default | | | Adjustment 1 | | | Adjustment2 | | |
|---|---|---|---|---|---|---|---|---|---|
| | **ML Through put** | **ML travel time** | **Avg R wait time** | **ML Through put** | **ML travel time** | **Avg R wait time** | **ML Through put** | **ML travel time** | **Avg R wait time** |
| Full HV | 1411 | 313.88 | 38.58 | 1411 | 313.88 | 38.58 | 1411 | 313.88 | 38.58 |
| Full ACC | 613 | 482.57 | 33.83 | 620 | 487.61 | **25.57** | **632** | **465.56** | 39.44 |
| Full AV | 1459 | 213.67 | 27.36 | 1459 | 213.67 | 27.36 | 1459 | 213.67 | 27.36 |
| High HV | 1104 | 399.64 | 46.45 | 1114 | 386.64 | 30.16 | **1138** | **378.68** | **25.85** |
| High ACC | 847 | 447.57 | 42.20 | 850 | 443.55 | **29.05** | **868** | **435.57** | 30.68 |
| High AV | 1375 | 365.1 | 35.82 | 1384 | 352.18 | 33.07 | **1400** | **354.04** | **27.75** |

**Table 27. Numerical results of the simulated scenarios for site 5.**

| Site 5 | Default | | | Adjustment 1 | | | Adjustment2 | | |
|---|---|---|---|---|---|---|---|---|---|
| | **ML Through put** | **ML travel time** | **Avg R wait time** | **ML Through put** | **ML travel time** | **Avg R wait time** | **ML Through put** | **ML travel time** | **Avg R wait time** |
| Full HV | 1311 | 385.22 | 142.31 | 1311 | 385.22 | 142.31 | 1311 | 385.22 | 142.31 |
| Full ACC | 473 | 652.34 | 88.88 | 504 | 519.8 | **65.87** | **532** | **513.88** | 87.24 |
| Full AV | 1550 | 177.04 | 21.42 | 1550 | 177.04 | 21.42 | 1550 | 177.04 | 21.42 |
| High HV | 834 | 610.34 | 143.51 | 823 | 629.7 | **126.93** | **847** | **599.08** | 156.95 |
| High ACC | 737 | 448.34 | 85.16 | 740 | 486.26 | **82.47** | **753** | **432.62** | 90.79 |
| High AV | 1457 | 228.66 | 69.90 | 1480 | 235.19 | **35.90** | **1538** | **228.66** | 89.52 |

## 5.4 Discussion of the results

The simulation results presented for proposed adjustments highlighted potential challenges in ramp metering performance at merge junctions, particularly when confronted with ACC mixed autonomy traffic flow. Overall, significant drops were observed in the ramp metering conditions as the number of ACC vehicles increased in the traffic, this is likely due to more conservation following behavior in ACC vehicles. However, the simulation of AV scenarios showed opportunities for ramp metering improvement. An improvement in the mainline throughput and travel time was observed as the MPR of AVs increased.

We proposed two adjustment scenarios based on the MnDOT's Density Adaptive Metering Algorithm by calculating the critical density, jam density, and capacity of the mixed autonomy in the defined mixed autonomy scenarios. However, it is important to note that our estimation of the fundamental diagram for mixed autonomy traffic is based on an analytical approach from car-following theory as we are still far from having mixed autonomy traffic with higher MPR of AVs compared to HVs on the roads, and empirical measurements are not yet possible.

The first adjustment considers updated values for critical density and jam density in the algorithm that is obtained from the fundamental diagram of mixed autonomy scenarios. The results of simulations show that this adjustment improves mainline throughput and travel time in some of the simulated scenarios compared to the default algorithm while significantly reducing ramp waiting times across all scenarios.

The second proposed adjustment further modifies the changing criteria of different ramp metering phases by updating the “low density” and “desired density” terms. The results of the simulations indicate that this adjustment improves the traffic flow on the mainline by increasing the throughput and decreasing the travel time. In most of the scenarios, the average wait time on the ramp is also decreased.

It is important to note that the adjusted algorithms maintain traffic flow conditions nearly identical to the default algorithm in Full AV scenarios. This is because the characteristics of automated vehicles reduce road congestion, preventing the ramp meter from being activated by current traffic demands. Therefore, we can conclude that a fully automated environment improves road capacity and allows more traffic to pass through. The simulation results provide important insights into how the MnDOT's Density Adaptive Metering Algorithm can be improved to be more effective in mixed-autonomy traffic flows.

Table 28 shows the percent change of each automation scenario under both algorithm adjustments suggested compared to the default algorithm for that automation scenario. As shown in Table 28, while the first adjustment demonstrates comparable or even superior performance in reducing average wait time on ramps, the second adjustment is more effective in enhancing traffic flow characteristics on the mainline.

**Table 28: Average percent change in performance metrics for each algorithm adjustment discussed across all five sites considered.**

| Scenario | Adjustment 1 | | | Adjustment2 | | |
|---|---|---|---|---|---|---|
| | ML Throughput (%) | ML travel time (%) | Avg Ramp wait time (%) | ML Throughput (%) | ML travel time (%) | Avg R wait time (%) |
| Full ACC | 4.79 | -5.71 | -25.34 | 9.47 | -10.63 | -22.58 |
| Full AV | 0.46 | -0.84 | -0.99 | 0.46 | -0.84 | -0.99 |
| High HV | -1.03 | 7.47 | -24.98 | 4.33 | -5.49 | -0.30 |
| High ACC | 1.20 | 0.81 | -21.79 | 2.88 | -3.27 | -24.12 |
| High AV | 1.43 | -2.13 | -28.12 | 3.20 | -3.98 | 2.14 |

# Chapter 6: Conclusions

This study used the MnDOT Density Adaptive Metering algorithm alongside traffic-flow data to simulate mixed-autonomy traffic across five real on-ramp sites in Minneapolis. Specifically, this study focused on the integration and impact of human-driven vehicles (HVs), adaptive cruise control (ACC) equipped vehicles, and fully autonomous vehicles (AVs) on the performance of the ramp metering sites. Our simulations provided a detailed analysis of how varying levels of vehicle automation influence ramp metering performance, particularly highlighting the challenges posed by ACC vehicles. These challenges are primarily due to the conservative following behavior inherent in ACC systems, which tend to reduce overall traffic throughput and increase inter-vehicle spacing, leading to significant drops in ramp metering efficiency.

However, the simulations also revealed that AVs offer opportunities to enhance the traffic flow on ramp meters. With increased market penetration of AVs, slight improvements in mainline throughput and travel times were observed, which indicates that future generations of automation could substantially optimize traffic flow and levels of service. In addition, the **Full CACC** scenario demonstrated exceptional performance across all key metrics, significantly surpassing other automation scenarios in terms of increasing the mainline throughput and reducing mainline travel time and ramp queue.

To better optimize roadway capacity, this study proposed adjustments to the MnDOT Density Adaptive Metering algorithm based on the car-following behavior observed in ACC and AV scenarios. These adjustments demonstrated a capability to improve mainline throughput and travel times while significantly reducing ramp waiting times across all vehicle types, compared to the default algorithm at mixed-autonomy traffic.

The insights gained underscore the importance of adapting ramp metering strategies to the shifting dynamics of vehicle automation. Future research should focus on refining these algorithms further, potentially through real-world trials and the development of real-time estimation techniques for the fundamental diagram that considers site-specific factors and the real-time composition of vehicle types. In addition, the remarkable potential of CACC vehicles should be explored further to assess their feasibility in large-scale implementation. Such advancements will be crucial in ensuring that ramp metering strategies remain effective as the landscape of vehicle automation continues to evolve.

The key takeaway points:

- Mixed-autonomy traffic will have different flow characteristics than current human-only traffic flow.
- The specific characteristics of the flow depend on the specific autonomy scenario (i.e., ACC, AV, etc.).
- MnDOT’s Density Adaptive Metering will continue to work; however, it may be less effective depending on the vehicle automation scenario.
- Small adjudgments to the settings in Density Adaptive Metering will allow for improved performance of ramp metering under different automation scenarios.

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