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Real-Time Prediction of Vehicle Locations in a Connected Vehicle Environment

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Final Report VCTIR 14-R4

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The wireless communication between vehicles and the transportation infrastructure, referred to as the connected vehicle environment, has the potential to improve driver safety and mobility drastically for drivers. However, the rollout of connected vehicle technologies in passenger vehicles is expected to last 30 years or more, during which time traffic will be a mix of vehicles equipped with the technology and vehicles that are not equipped with the technology. Most mobility applications tested in simulation, such as traffic signal control and performance measurement, show greater benefits as a larger percentage of vehicles are equipped with connected vehicle technologies.

The purpose of this study was to develop and investigate techniques to estimate the positions of unequipped vehicles based on the behaviors of equipped vehicles. Two algorithms were developed for this purpose: one for use with arterials and one for use with freeways. Both algorithms were able to estimate the positions of a portion of unequipped vehicles in the same lane within a longitudinal distance. Further, two connected vehicle mobility applications were able to use these estimates to produce small performance improvements in simulation at low penetration rates of connected vehicle technologies when compared to using connected vehicle data alone, with up to an 8% reduction in delay for a ramp metering application and a 4.4% reduction in delay for a traffic signal control application.

The study recommends that the Virginia Center for Transportation Innovation and Research (VCTIR) continue to assess the data quality of connected vehicle field deployments to determine if the developed algorithms can be deployed. If data quality is deemed acceptable and if a connected vehicle application is tested in a field deployment, VCTIR should evaluate the use of the location estimation algorithms to improve the application's performance at low penetration rates. This is expected to result in reduced delays and improved flow for connected vehicle mobility applications during times when few vehicles are able to communicate wirelessly.

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FINAL REPORT

REAL-TIME PREDICTION OF VEHICLE LOCATIONS IN A CONNECTED VEHICLE ENVIRONMENT

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(A partnership of the Virginia Department of Transportation
and the University of Virginia since 1948)

Charlottesville, Virginia

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DISCLAIMER

ABSTRACT

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LIST OF ACRONYMS

EV	equipped vehicle
FHWA	Federal Highway Administration
GPS	global positioning system
LE-dft	Location Estimation, Default Turning Movements
LE-msrd	Location Estimation, Measured Turning Movements
MAE	mean absolute error
NGSIM	Next Generation Simulation
PMSA	predictive microscopic simulation algorithm
SAE	Society of Automotive Engineers
VCTIR	Virginia Center for Transportation Innovation and Research
VDOT	Virginia Department of Transportation

FINAL REPORT

REAL-TIME PREDICTION OF VEHICLE LOCATIONS IN A CONNECTED VEHICLE ENVIRONMENT

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INTRODUCTION

The concept of connected vehicles—previously known as IntelliDrive or Vehicle Infrastructure Integration—uses advanced wireless communications, global positioning systems (GPS), vehicle sensors, and smart infrastructure to allow vehicles and the infrastructure to communicate wirelessly. In a connected vehicle environment, a vehicle equipped with the technology can share its location, speed, heading, and many other data in real time with nearby equipped vehicles and the surrounding infrastructure via wireless communications. There are several pilot deployments of connected vehicle technology, including test beds in Fairfax County, Virginia, and in Blacksburg, Virginia, on the Virginia Smart Road and Route 460 (Connected Vehicle/Infrastructure University Transportation Center, 2012).

Researchers have developed several transportation applications that use the data from connected vehicles to improve safety and mobility, such as traffic signal control (Smith et al., 2011) and automated incident detection (Barria and Thajchayapong, 2011). Because of the gradual rollout of connected vehicle technologies, researchers often study the effect of different penetration rates of connected vehicle technologies on an application's performance. In many connected vehicle mobility applications, the performance of the application improves as the percentage of vehicles equipped with communication devices increases. For example, the traffic signal control algorithm PAMSCOD (platoon-based arterial multi-modal signal control with online data) reduced delay by an additional 12% when the penetration rate increased from 20% to 60% (He et al., 2012). Priemer and Friedrich (2009) found a 6.5% improvement in vehicle speeds when the penetration rate increased from 10% to 50% in their traffic signal control algorithm.

Not only do connected vehicle applications perform better at higher connected vehicle penetration rates, many are also unable to outperform traditional applications at low penetration rates. The minimum required penetration rate needed to demonstrate any benefit varies based on the application but is typically near 20% to 30%, as seen in Table 1.

The problem of low penetration rates is of particular concern because of the expected gradual introduction of connected vehicles. Were a federal mandate to be issued requiring all new vehicles sold in the U.S. be equipped with connected vehicle technologies, the John A. Volpe National Transportation Systems Center (2008) estimates that it would take 9 years after a before 50% of vehicles on the roadway were able to communicate. The anticipated penetration rate over time is shown in Figure 1.

Table 1. Connected Vehicle Applications and Corresponding Minimum Required Equipped Vehicle Penetration Rates

Application	Minimum Equipped Vehicle Penetration Rate (%)
Traffic signal control[a-c]	20-30
Freeway incident detection[d]	20
Lane-level speed estimation[e]	20
Arterial performance measurement[f]	10-50
Queue length estimation[g]	30

[a] Smith et al. (2011).
[b] He et al. (2012).
[c] Priemer and Friedrich (2009).
[d] Barria and Thajchayapong (2011).
[e] Rim et al. (2011).
[f] Li et al. (2008).
[g] Ban et al. (2011).

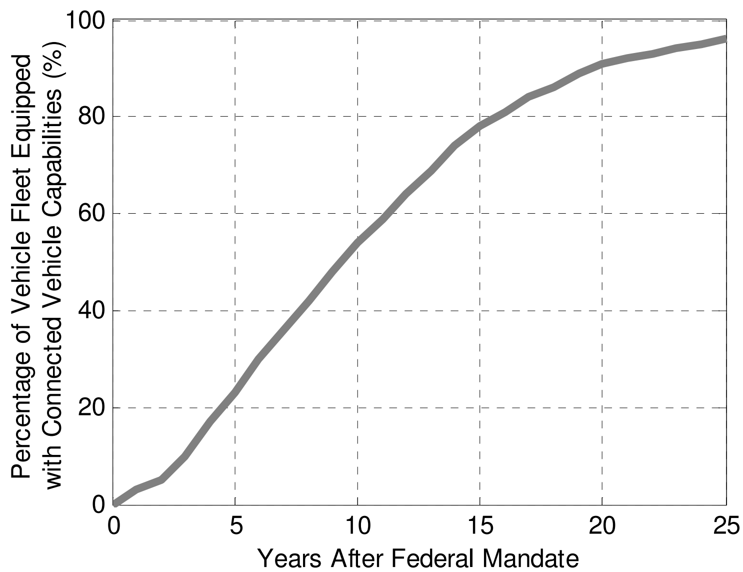

Figure 1. Anticipated Penetration Rate of Connected Vehicle Capabilities After Federal Mandate, Were One to Be Issued, for Installation in All New Vehicles Sold in the U.S. (John A. Volpe National Transportation Systems Center, 2008).

The use of aftermarket devices, which can be used to retrofit existing vehicles, may shorten this timeline somewhat. Another option is the use of alternative technologies, such as smart phones equipped with GPS receivers. However, even with these technologies, bandwidth shortages and battery life may restrict full adoption. In any scenario, there will likely be a transition period where only a portion of vehicles are equipped. Researchers have developed several ways to supplement connected vehicle data by using video to detect unequipped vehicles (Richardson, 2011), but these solutions require additional infrastructure with limited range.

Simulation testing has shown that when more vehicles can report their location, the performance of connected vehicle mobility applications improves. The research presented in this report explored two follow-up questions:

1. Can the locations of some unequipped vehicles be estimated from the behavior of a few equipped vehicles (EVs)?

2. If the answer to Question 1 is in the affirmative, can these estimated locations be used to improve the performance of connected vehicle mobility applications?

If both questions can be answered in the affirmative, the performance of some connected vehicle applications can be improved at low penetration rates merely by analyzing data from a few EVs, estimating the positions of unequipped vehicles, and feeding these estimates back into the applications. These applications' performances could be improved with minimal associated cost.

Several terms with regard to vehicles are used throughout this report and are defined here.

- *Connected vehicles:* the system of wireless communications among vehicles and the infrastructure.

- *Equipped vehicles:* vehicles that are equipped with the necessary hardware and software and are participating in the connected vehicle system.

- *Unequipped vehicles:* vehicles that are not able to participate in a connected vehicle system because of a lack of equipment, equipment failure, or bandwidth restrictions.

- *Inserted vehicles:* vehicles that exist only in a simulation and that represent the location algorithms' estimates of the positions of unequipped vehicles.

PURPOSE AND SCOPE

A high-level goal of VDOT is to improve safety and traffic flow as effectively and inexpensively as possible. The purpose of this study was to develop and investigate techniques to estimate the positions of unequipped vehicles based on the behaviors of EVs in a connected vehicle environment. This study was undertaken in the hope that these techniques, by providing sophisticated estimates of unequipped vehicle locations, could improve the performance of other proposed connected vehicle mobility applications at low penetration rates.

The objectives of this study were as follows:

1. Develop algorithms to estimate the locations of a portion of unequipped vehicles in a connected vehicle environment.

2. Evaluate the performance of these algorithms based on their accuracy and their ability to improve the performance of connected vehicle mobility applications.

3. Ensure that the algorithms are realistic, feasible, and implementable in a connected vehicle environment.

The scope was limited to available, empirical vehicle trajectory datasets and calibrated, available simulation data.

METHODS

Overview

Four tasks were carried out to achieve the study objectives:

1. literature review
2. development of freeway and arterial location estimation algorithms
3. development of testing parameters for the developed algorithms
4. testing and evaluation of the developed algorithms.

Task 1: Literature Review

The literature was reviewed to determine similar proposed techniques to estimate positions of individual unequipped vehicles in a connected vehicle environment at low penetration rates. Additional literature was reviewed to allow a better understanding of car-following models and connected vehicle technology and to identify connected vehicle mobility applications that could benefit from position estimates of individual unequipped vehicles.

Task 2: Development of Freeway and Arterial Location Estimation Algorithms

Two algorithms were developed to estimate the positions of unequipped vehicles based on the behaviors of EVs. One algorithm was developed for freeway environments (where vehicles react primarily to other vehicles) and the other for arterial environments (where vehicles often queue at traffic signals). The algorithms were designed to be as generic as possible, with minimal calibration to specific road networks.

Task 3: Development of Testing Parameters for Developed Algorithms

The next phase of the research plan was to develop the parameters that would be used in testing the algorithms. Many of the parameters were defined early, such as the evaluation network, number of simulation repetitions, and connected vehicle application. Others were identified during Task 4, such as sensitivity of an estimated vehicle’s lifespan on freeways.

Task 4: Testing and Evaluation of Developed Algorithms

The developed algorithms were tested extensively. The freeway location estimation algorithm was tested using vehicle trajectory data from the Next Generation Simulation (NGSIM) project, a field-collected dataset of individual vehicle movements along several corridors in the United States (Federal Highway Administration [FHWA], 2010), and the arterial location estimation algorithm was tested on data generated from microscopic simulation. In all tested scenarios, multiple simulation runs were evaluated with unique random seeds, and results were ensured to be within 10% of the mean at a 95% confidence level. In addition, various penetration rates were tested, ranging from 5% to 100%. Then, each algorithm was applied to an existing connected vehicle mobility application (signal control for the arterial location estimation algorithm, and ramp metering for the freeway location estimation algorithm) to determine if the location estimation algorithms developed could improve the performance of these applications at low EV penetration rates.

RESULTS AND DISCUSSION

Task 1: Literature Review

Several algorithms have been developed to estimate the location of either individual vehicles or high resolution vehicle densities based on the behavior of a small subset of sampled vehicle trajectories, often referred to as probe vehicles. Preliminary work focused on estimating freeway travel states rather than individual vehicle locations. The earliest work was based on vehicle location and travel time information as determined from cell tower signal triangulation (Bargera, 2007; Sanwal and Walrand, 1995; Westerman et al., 1996). Later work focused on much more accurate, although sparsely collected, GPS data (Krause et al., 2008). Mobile sensor data were eventually integrated with point detection data and used to estimate vehicle travel time (Nanthawichit et al., 2003).

Herrera and Bayen (2010) used Kalman filtering techniques and Newtonian relaxation to integrate point detection and mobile sensors into a high resolution traffic state estimation of a freeway. Their algorithms were evaluated using both empirical ground truth freeway data ([FHWA, 2010) and actual in-vehicle cell phones with GPS receivers (Herrera et al., 2008). They were able to estimate vehicle densities of multilane 120-foot segments with a root-mean-square error of 1.78 to 2.44 vehicles depending on assumptions, but they did not estimate individual vehicle locations, as the goal of their research was a more accurate estimation of freeway status between point detectors.

On arterials, Ban et al. (2011) used the reported travel times of a portion of vehicles traveling through an intersection to calculate their individual delays. This information was then used to determine the amount of time each vehicle was in the signal's queue. Using this information, Ban et al. (2011) could estimate the arrival rate at the intersection and by assuming uniform flow rate and constant discharge rate could estimate the total length of the queue with only 30% of vehicles reporting their locations. Their procedure required two restrictive assumptions: (1) that the arrival between two vehicles in one cycle was the uniform arrival rate across the entire cycle, and (2) that the penetration rate was relatively high so that there were at least two queued vehicles per cycle per approach. The authors acknowledged that these assumptions limit the ability to deploy the system in the field. In addition, the sampled vehicle must first pass a virtual trip line downstream of the intersection, which delays the estimation of the queue length by several seconds. The mean absolute percentage error of the number of vehicles in a queue ranged from 21% to 23% during uncongested conditions and from 14% to 17% during congested conditions. The algorithm was tested using a participating vehicle penetration rate from 20% to 100%.

Building on the queue length estimation technique, Sun and Ban (2011) attempted to predict the locations of and trajectories on un-sampled vehicles from a location upstream of the intersection to the stop bar based on the location of approaching vehicles. They first assumed a uniform arrival of un-sampled vehicles between any two consecutive sampled vehicles, rather than a uniform arrival for the entire time period as in previous work (Ban et al., 2011). The number of vehicles arriving between two sampled vehicles was also known, implying the presence of an upstream detector. The vehicle arrival rate along with the known signal timing was used to estimate the shockwave boundary. Once the shockwave boundary had been plotted on a time-space diagram, the trajectories of un-sampled vehicles were predicted using several simplified assumptions: they maintain free flow speed until reaching the back of the queue; come to an immediate stop while in the queue; and travel at free flow speed once the queue is discharged. Individual vehicle accelerations were ignored. The algorithm was tested on simulation data, where the root-mean-square error of the time-position of unequipped vehicles was found to be 2.8 seconds at a 20% connected vehicle penetration rate and a free-flow speed of 40 miles per hour (17.9 meters per second). The algorithm was also tested on the NGSIM data (FHWA, 2010), where a root-mean-square error of 8.1 seconds was found at a 20% penetration rate.

In summary, of the unequipped vehicle location estimation techniques discussed in this literature review, all had one or more of the following three shortcomings:

1. They aggregated estimated vehicle locations spatially.

2. They used unrealistic vehicle behaviors in their models.

3. They did not estimate vehicle movements over a distance beyond a small study area of a few meters.

The location estimation techniques developed as part of this research were designed to overcome these shortcomings.

Task 2: Development of Freeway and Arterial Location Estimation Algorithms

Two algorithms were developed to estimate the positions of unequipped vehicles, one for arterial roadways and one for freeways.

Arterial Location Estimation

A four-step procedure was used to estimate the positions of unequipped vehicles:

1. Determine from its observed behavior when an EV is reacting to a previously unobserved unequipped vehicle via gaps in a stopped queue.

2. Estimate the unequipped vehicle's initial position and speed, and insert it into a rolling, real-time simulation of the vehicles on the network.

3. Simulate the movements of the inserted vehicle over time.

4. Determine when the inserted vehicle estimate is no longer correct, and remove it from the simulation.

Step 1: Determine from its observed behavior when an EV is reacting to a previously unobserved unequipped vehicle via gaps in a stopped queue.

The first step in estimating the locations of unequipped vehicles is to determine when an EV's behavior indicates the presence of a previously undetected unequipped vehicle. On an arterial, the most obvious example of this unexpected behavior occurs in a stopped queue, shown in Figure 2. If an EV leaves a large gap between itself and the leading vehicle at any time or between itself and the stop bar during a red phase, an unequipped vehicle is probably in the gap.

In this step, the algorithm finds all stopped vehicles (both EVs and vehicle estimates inserted during previous time steps) within 50 meters (164 feet) of the stop bar on an approach. Figure 3 shows how the queue length is calculated. *Stopped vehicles* are defined as vehicles with a speed of less than 1 meter per second. If the signal is red, the start of the queue is the location of the stop bar. If the signal is amber or green, the start of the queue is the location of the front of the stopped vehicle nearest the stop bar. The end of the queue is the location of the front of the stopped vehicle that is both farthest from and within 50 meters (164 feet) of the stop bar. The vehicles at the start and end of the queue may be in different lanes.

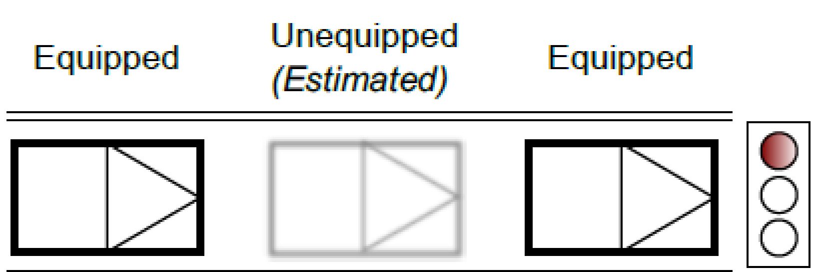

Figure 2. Existence and Location of Unequipped Vehicle Estimated From Gaps in Stopped Queue of 2 Vehicles Equipped With Communication Devices. This often occurs during the red phase.

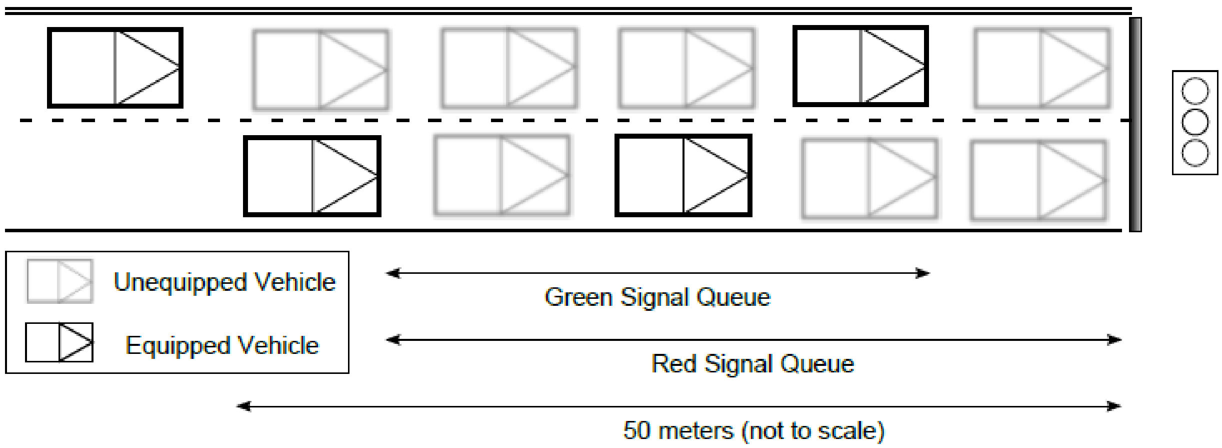

Figure 3. Queue Length As Calculated in Developed Arterial Location Estimation Algorithm for Green and Red Phases. Figure is not drawn to scale.

Once the beginning and end of the queue are determined, the vehicle positions within the queue are analyzed to find gaps. Vehicles in this analysis were assumed to behave in accordance with the Wiedemann car-following model, discussed in greater detail later. According to this model and based on the empirical values collected by Wiedemann and Reiter (1992) (and in some cases extrapolated from Wiedemann and Reiter's charts by Olstam and Tapani [2004]), the minimum gap between two observed vehicles that will trigger an insertion is 2 × AX = 14.5 meters (48 feet), where *AX* represents the average stopped space headway. After each new estimated vehicle is inserted, the queue is again searched for gaps until none is present.

Step 2: Estimate the unequipped vehicle's initial position and speed, and insert it into a rolling, real-time simulation of the vehicles on the network.

When a gap is found in the queue, an estimated vehicle is inserted into the queue. The vehicle is inserted at the average stopped following distance *AX* predicted from the Wiedemann model (Wiedemann and Reiter, 1992), which is 7.25 meters (24 feet) behind the front of the leading observed vehicle. This assumes that the leading vehicle has a typical passenger vehicle length of 4.75 meters (16 feet) and the gap between vehicles is 2.5 meters (8 feet).

In the evaluation of this network, a system with uniform vehicle lengths was used. All inserted vehicles were assigned a length of 4.75 meters (16 feet). Because all inserted vehicles were in stopped queues, the inserted vehicle had a speed of 0 m/s (0 mph) and an acceleration of 0 m/s^2 (0 ft/s^2). If the vehicle-to-infrastructure communication system is able to transmit individual vehicle lengths, the inserted vehicle will be placed with its front bumper 2.5 meters (8 feet) behind the rear bumper of the lead vehicle.

Step 3: Simulate the movements of the inserted vehicle over time.

Once the vehicles are inserted into the gaps, their movements and interactions with other equipped and inserted vehicles can be simulated. This allows the arterial location estimation algorithm to continue to estimate unequipped vehicle positions even as the inserted vehicle leaves the queue and travels through the network. The microscopic simulation software VISSIM was used to simulate vehicle movements (PTV AG, 2011). VISSIM was chosen because of its COM (Component Object Model) Interface, which allows the user to insert and delete individual vehicles without stopping the simulation run. In addition, VISSIM allows the user to open and control multiple simulation instances simultaneously, allowing the behavior of one model to influence the inputs to the other. This was a particularly useful capability in the evaluation of the effect of the arterial location estimation algorithm on a connected vehicle application, as a single simulation run can represent ground truth and another can represent a rolling estimation of vehicle positions.

Step 4: Determine when the inserted vehicle estimate is no longer correct, and remove it from the simulation.

Vehicle estimates that have been inserted into the simulation are checked every time step to ensure that their positions have not been overlapped by an EV's self-reported position. *Overlap* is defined as vehicles making physical contact and uses the assumed vehicle lengths of inserted vehicles and reported vehicle lengths of EVs. Once an inserted vehicle has been overlapped, it is no longer considered a correct estimate of an actual unequipped vehicle and is therefore removed from the simulation. Inserted vehicles that reach the end of the network are also deleted from the simulation.

Freeway Location Estimation

There are several differences between the developed arterial and freeway location estimation algorithms. On arterials, the presence of unequipped vehicles can be estimated based on gaps in a queue of EVs. On freeways, vehicles may often accelerate and decelerate, but complete stops are infrequent outside the most congested urban areas or during incidents. However, freeways are unique in that they represent a controlled access, vehicle-only environment. Freeway drivers react mostly to other vehicles in the roadway, with occasional exceptions such as weather, glare, incidents, etc. Therefore, any unusual longitudinal behavior exhibited by a vehicle is likely a response to the vehicle or vehicles directly ahead rather than to traffic control devices.

In the developed arterial location estimation algorithm, an unequipped vehicle was assumed to be present in the gaps of a queue. At a simpler level, the presence was assumed not because of the gap but because the equipped following vehicle did not accelerate into the gap as expected. The differences in an EV's actual and expected behavior may indicate the presence of an unequipped vehicle. On freeways, the longitudinal acceleration behavior of vehicles can be used to estimate vehicle locations directly if one assumes that an EV must be reacting to another vehicle.

To develop a microscopic estimation of freeway vehicle locations and speeds, the freeway location estimation algorithm determines when an EV is behaving differently than would be expected based on the locations and speeds of vehicles directly ahead. To identify this unexpected behavior, a definition of *expected behavior* is needed. A car-following model, which predicts the behavior of vehicles in response to a vehicle or vehicles ahead, can serve as a baseline for expected behavior. For this study, the Wiedemann model was selected, as discussed here.

Overview of Wiedemann Model

The Wiedemann model, as cited by Olstam and Tapani (2004), is a psychophysical car-following model that estimates the thresholds for a driver's decision to accelerate or decelerate based on the driver's perceptions of changes in relative velocity. The model uses four regimes: free driving, following, closing, and emergency; each regime corresponds to a vehicle's position and speed relative to the vehicle directly ahead.

The Wiedemann model was selected for two reasons:

1. It is space- and time-discrete and is therefore compatible with the freeway location estimation algorithm as implemented.

2. It has gained acceptance as the basis for VISSIM (PTV AG, 2011), which is widely used.

The Wiedemann model has several parameters to determine a vehicle's regime and the corresponding rate of acceleration. To avoid overfitting the model to the evaluation dataset, the Wiedemann model as applied here used the calibration parameters derived from empirical freeway data collected by Wiedemann and Reiter (1992). Some model parameters were found in the original paper (Wiedemann and Reiter, 1992), and others were extrapolated from Wiedemann and Reiter's charts by Olstam and Tapani (2004). Specific values are provided in Table 2.

In the freeway location estimation algorithm, the Wiedemann model is limited to in-lane car-following; lane changing decisions are not modeled, as these models introduce additional, and potentially unnecessary, complexity into the algorithm. Theoretically, an unequipped vehicle that changes lanes will be represented by two separate inserted vehicles, created and deleted in separate lanes and at different times.

Once the model parameters have been determined for each vehicle at each time step, the vehicle must then be categorized into one of the four regimes, which will then determine its new rate of acceleration. Figure 4 demonstrates the decision process to select the correct regime given the vehicle's parameters.

In the free regime, the vehicle accelerates at the rate needed to reach its desired speed, bounded by the maximum acceleration rate. The acceleration rate is defined in Equation 1.

$$a_n = \min\{a_{\max}, v_{\text{des}} - v_n\} \qquad \text{[Eq. 1]}$$

For the emergency regime, the vehicle attempts to slow as quickly as possible to avoid a collision. The acceleration rate for the emergency regime is defined in Equation 2.

$$a_n = \frac{1}{2} \cdot \frac{\Delta v^2}{AX - \Delta x} + a_{n-1} + a_{\min} \frac{ABX - \Delta x}{BX} \quad \text{[Eq. 2]}$$

In the closing regime, defined in Equation 3, the vehicle decelerates at a rate designed to begin following the lead vehicle.

$$a_n = \max\left\{ \frac{1}{2} \cdot \frac{\Delta v^2}{ABX - \Delta x} + a_{n-1}, a_{\min} \right\} \quad \text{[Eq. 3]}$$

In the following regime, defined by Equation 4, the vehicle maintains its speed with an acceleration of zero.

$$a_n = 0 \quad \text{[Eq. 4]}$$

Table 2. Wiedemann Model Simulation Parameters and Assumed Vehicle Characteristics

Parameter	Description	Value Used	Unit
τ	Acceleration difference threshold	1.96	m/s^2
Δx	Headway	$x_{n-1} - x_n$	m
Δv	Relative velocity	$v_n - v_{n-1}$	m/s
l_n, l_{n-1}	Length of vehicle	4.75	m
a_{n-1}	Initial acceleration of inserted vehicle	0.0	m/s
V	Min speed of vehicle and leader	$\min\{v_n, v_{n-1}\}$	m/s
AX	Min headway	$l_n + 2.5 = 7.25$	m
BX	Calibration factor	$2.5\sqrt{v}$	-
ABX	Desired min headway at low Δv	$AX + BX = 7.25 + 2.5\sqrt{v}$	m
CX	Calibration factor	40	-
EX	Calibration factor	1.5	-
a_{max}	Max acceleration	$3.5 - \frac{3.5}{40} v$	m/s^2
a_{min}	Min acceleration	$-20 + \frac{1.5}{60} v$	m/s^2
SDX	Maximum following distance	$AX + EX \times BX = 7.25 + 3.75\sqrt{v}$	m
SDV	Decreasing speed difference	$\left(\frac{\Delta x - AX}{CX}\right)^2 = \left(\frac{\Delta x - 7.25}{40}\right)^2$	m/s
$OPDV$	Increasing speed difference	$-2.25SDV$	m/s
$CLDV$	Small decreasing speed difference	Equal to *SDV*, as in VISSIM	m/s^2
λ	Leading vehicle speed adjustment factor	0.162	-

Stochastic values in the original model (Wiedemann and Reiter, 1992) were removed for simplicity. All parameters were developed from Wiedemann and Reiter (1992) as interpreted by Olstam and Tapani (2004), with the exception of λ and τ, which were developed as part of this study.

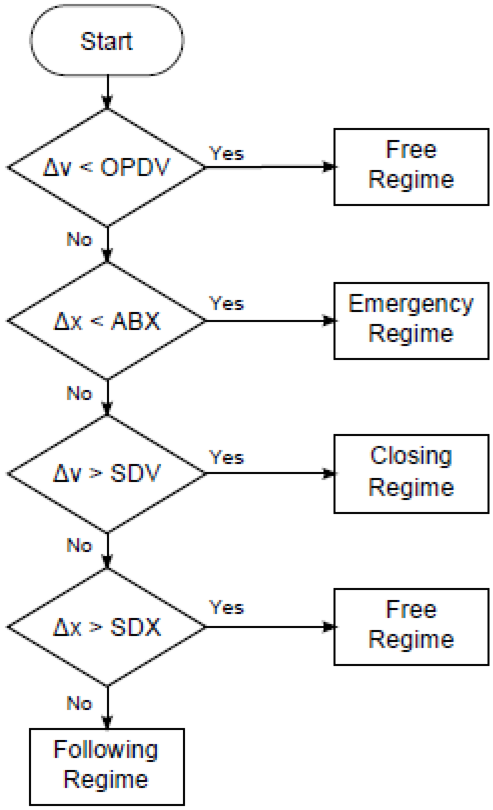

Figure 4. Decision Flowchart to Select Vehicle's Regime in Wiedemann Car-Following Model (Wiedemann and Reiter, 1992). Individual terms are defined in Table 2.

Freeway Location Estimation Algorithm Procedure

The procedure to predict the location of vehicles is a five-step process.

1. Each second, the locations, speeds, and accelerations of all EVs at a given time t are placed in a virtual roadway (i.e., the simulation), which is already populated with inserted vehicle estimates from previous time steps.

2. Any inserted vehicles that have been overlapped by the new EVs are removed from the simulation.

3. For each remaining vehicle in the simulation, both EVs and inserted estimates, its expected position is updated to time $t + 1$ based on the Wiedemann model. Each vehicle reacts to the nearest vehicle ahead in the same lane at time t, regardless of whether the vehicle is an EV or an inserted vehicle.

4. The rate of acceleration for each EV as defined by the Wiedemann model is compared to the EV's actual self-reported rate of acceleration from Step 1. If the actual acceleration is less than the predicted acceleration by a predefined threshold τ, it is assumed that the EV is reacting to a previously undetected unequipped vehicle.

5. The new vehicle is then inserted into the simulation at the estimated location and speed, assuming it does not already overlap with another inserted vehicle or EV. The inserted vehicle will continue to move forward according to Step 3 until it is overlapped or leaves the network.

Step 5, the insertion of new vehicles at the estimated location and speed, requires further explanation. As discussed, if an EV is found to have an acceleration that is less than expected by a predetermined threshold τ (called the acceleration difference threshold, as discussed later), it is assumed that the EV is reacting to a previously undetected unequipped vehicle. This EV that triggered the insertion is assumed to behave according to the Wiedemann model and is reacting to another vehicle. Therefore, it is assumed that the vehicle is in either the closing or following regime, as the free regime does not react to vehicles and the emergency regime rarely occurs. If the triggering EV is traveling faster than the estimated unequipped vehicle, it is assigned the closing regime, and if it is traveling slower than the lead vehicle, it is assigned the following regime.

Speed Estimation

The speed of the unequipped vehicle cannot be directly observed and must be estimated. A relationship among lead vehicle speed, following vehicle speed, and following vehicle acceleration is defined in Equation 5.

$$v_{n-1} = \max\{v_n + \lambda a_n, 0\} \qquad \text{[Eq. 5]}$$

where

v_{n-1} = speed of the unequipped lead vehicle (m/s)
v_n = speed of the equipped following vehicle (m/s)
a_n = acceleration of the equipped following vehicle (m/s^2)
λ = calibration factor.

Using linear regression on the NGSIM dataset (FHWA, 2010) of empirical vehicle trajectories, $\lambda = 0.162$ when using m/s and m/s^2 for speed and acceleration, respectively, with $R^2 = 0.831$. When using U.S. customary units of mph and ft/s^2 for acceleration, $\lambda = 0.795$. This value was used in all evaluations, regardless of network.

Acceleration Estimation

If $v_{n-1} < v_n$, the closing regime is used to determine the unequipped vehicle's position. The formula for acceleration of vehicle n is defined in Equation 6.

$$a_n = \frac{1}{2} \cdot \frac{(\Delta v)^2}{ABX - \Delta x} + a_{n-1} \qquad \text{[Eq. 6]}$$

where

ABX = desired minimum space headway at low speed differences (m)

Δv = difference in speed between vehicle n (the equipped following vehicle) and vehicle n-1 (the lead vehicle) (m/s)

Δx = space headway between vehicle n and vehicle n-1 (m)

a_{n-1} = acceleration of lead vehicle n-1.

Because the actual acceleration a_n of vehicle n is known, Equation 5 can be rearranged to determine the space headway, thereby predicting the location of the leading vehicle n-1. The lead vehicle's speed was estimated from Equation 5, and Δv can be determined from Equation 7.

$$\Delta v = v_n - v_{n-1} = \min\{-\lambda a_n, v_n\} \qquad \text{[Eq. 7]}$$

Uniform Vehicle Length Assumption

The leading vehicle is assumed to have an acceleration of zero and a standard vehicle length of 4.75 meters (16 feet). The vehicle length assumption is somewhat restrictive, as it may overestimate the number of unequipped vehicles when truck percentages are high. This assumption was made for several reasons. First, because the test networks have very low truck percentages, the uniform vehicle length assumption simplifies the model. Second, although the Society of Automotive Engineers (SAE) dedicated short-range communications (DSRC) standard (Standard J2735) to be used in a connected vehicle environment includes vehicle size in its Basic Safety Message (i.e., BSM) (SAE, 2009), vehicle size information may not be included in other wireless communication standards. Finally, mistaking a truck for two smaller vehicles may have minimal impact on the performance of the model. The *Highway Capacity Manual* uses a passenger car equivalent E_T to represent trucks and buses when calculating freeway capacity. Each truck or bus is represented by 1.5 passenger vehicles on flat terrain, 2.5 vehicles on rolling terrain, and 4.5 vehicles on mountainous terrain (Transportation Research Board, 2010). Using a 20-meter (66-foot) tractor trailer as an example (FHWA, 2004) and using the equation for desired headway ABX from Table 2, two vehicles of 4.75 meters (16 feet) will take the place of a single truck when speeds are less than or equal to 4.55 m/s (10.2 mph), as demonstrated in Equation 8.

$$7.25 + 3.75\sqrt{v} + 4.75 \leq 20 \qquad \text{[Eq. 8]}$$

When speeds are greater than 4.55 m/s (10.2 mph), only one vehicle will represent each truck. Therefore, each truck will be represented by between 1 and 2 vehicles, similar to the passenger car equivalent factor for flat terrain in the *Highway Capacity Manual.*

Position Estimation

Equation 9 demonstrates the rearrangement of Wiedemann and Reiter's (1992) closing acceleration equation using the new assumptions for leading vehicle acceleration a_{n-1} and length l_{n-1}.

$$\Delta x = ABX - \frac{1}{2} \cdot \frac{\left(\min\{-\lambda a_n, v_n\}\right)^2}{a_n} \qquad \text{[Eq. 9]}$$

Equations 6 through 9 assume that because $v_{n-1} < v_n$, vehicle n must be in the closing regime. Alternatively, if the lead vehicle's speed is estimated to be greater than or equal to the following vehicle's speed, i.e., $v_{n-1} > v_n$ or $a_n \geq 0$, the following vehicle is assumed to be in the following regime. The space headway is simply the desired minimum space headway *ABX* as defined in Equation 10.

$$\Delta x = ABX \qquad \text{[Eq. 10]}$$

By assuming the unequipped vehicle's speed using Equation 5 and assuming its acceleration of zero, the headway of the two vehicles is calculated and the lead vehicle is inserted at the appropriate location and speed. The new vehicle's location can be found using Equation 11.

$$x_{n-1} = x_n + \Delta x \qquad \text{[Eq. 11]}$$

Rolling Estimation

The inserted vehicle exists in the rolling estimation of the traffic network and continues to move forward and interact with other equipped and unequipped vehicles according to the Wiedemann car-following model without changing lanes. The inserted vehicle is removed from the simulation when an EV no longer reacts to it, the inserted vehicle overlaps positions, or the inserted vehicle leaves the network.

Acceleration Difference Threshold

The acceleration difference threshold τ that initiates a vehicle insertion is a critical value in the analysis, and for all testing $\tau = 0.2$ g (1.96 m/s^2, 6.43 ft/s^2). This value was chosen based on the threshold of 0.5 g for determining a potential incident in naturalistic driving studies (Dingus et al., 2006). In addition, the car-following model used here has a maximum acceleration of 0.36 g (3.5 m/s^2, 11.5 ft/s^2) when a vehicle is stopped, with this maximum rate of acceleration inversely related to the vehicle's speed. Therefore, any vehicle traveling less than 17.6 m/s (39 mph) with no acceleration but with a predicted maximum acceleration (a_{max}) will cause the algorithm to insert an unequipped vehicle. This value is calculated from the equation for maximum acceleration in Table 2, where 1.96 = 3.5 - (3.5/40)(17.6). In this way, the algorithm is effective at low-speed synchronized traffic flow, even when vehicles are not decelerating.

Vehicle Data Quality

Finally, the algorithm assumes that EVs report their lane; location; speed (which if not reported directly can be determined from the difference in location since the last transmission); and instantaneous acceleration. In a dedicated short-range communications (DSRC) radio-enabled environment, this information would be included in the Basic Safety Message (BSM), transmitted by each vehicle 10 times per second for crash avoidance applications as described in SAE J2735 (SAE, 2009). The freeway location estimation algorithm requires that vehicles report only once per second, as this allows for the periodic message drops expected in the BSM's 10 Hz transmission rate. The algorithm assumes EVs will be able to report their own lane-level locations, as determined via GPS, a global navigation satellite system, or some other means. Although GPS alone cannot reliably determine location at this level of precision, when supplemented by Russia's GLONASS and forthcoming satellite systems from Europe (Galileo) and China, it is expected to achieve an accuracy of 1.5 meters (5 feet) 95% of the time, even in urban canyons, by 2020 (Popovic and Bai, 2011). This level of accuracy should be adequate for the lane-level positioning needed for the freeway location estimation algorithm.

Privacy

It is worth noting the algorithm was designed to protect driver privacy as much as possible. Although polled often, vehicles are never re-identified in the corridor, and the algorithm by design does not need to store vehicle trajectories for longer than 1 second. In a field implementation, the system can be designed to delete immediately or specifically not request individual vehicle IDs and can also be designed with minimal internal memory to ensure that EV locations are not stored any longer than necessary.

Brief Demonstration of Algorithm

Figure 5 provides an example using two vehicles to demonstrate the algorithm. The lead vehicle travels at 20 m/s (45 mph) and the following vehicle at 15 m/s (34 mph), with a headway of 100 m (328 feet). Using the equation for maximum following distance SDX in Table 2, the vehicle's SDX can be calculated, as demonstrated in Equations 12 and 13.

$$v = \min\{v_n, v_{n-1}\} = \min\{15, 20\} = 15\text{m/s} \qquad \text{[Eq. 12]}$$

$$SDX = 7.25 + 3.75\sqrt{v} = 7.25 + 3.75\sqrt{15} = 21.77\text{m} \qquad \text{[Eq. 13]}$$

Because the actual headway of 100 meters (328 feet) is greater than SDX ($\Delta x > SDX$) and because the speed differential is negative ($\Delta v = v_n - v_{n-1} < 0$), according to Table 2 the following vehicle is in the free regime. In a software program, the decision process in Figure 4 would be used to determine a vehicle's regime. Using the equation for expected acceleration of a vehicle in the free regime, Equation 1, the acceleration is calculated as shown in Equation 14.

$$a_n = 3.5 - \frac{3.5}{40}\sqrt{15} = 2.18\text{m/s}^2 \qquad \text{[Eq. 14]}$$

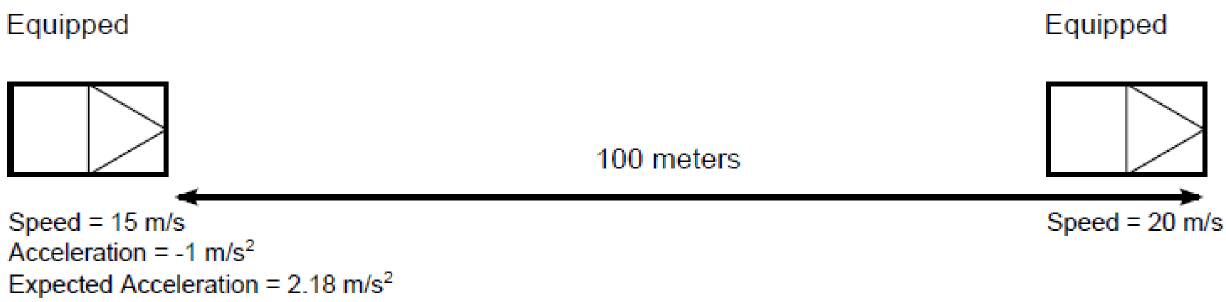

Figure 5. Example of Freeway Location Estimation Algorithm Showing Two Equipped Vehicles Before Estimation of Location and Speed of an Unequipped Vehicle

The actual acceleration of -1 m/s^2 (-3.3 ft/s^2) is less than the expected acceleration of 2.18 m/s^2 (7.2 ft/s^2) by 3.18 m/s^2 (10.4 ft/s^2), which exceeds the acceleration difference threshold τ of 2 g = 1.96 m/s^2 (6.4 ft/s^2). Therefore, a vehicle insertion is triggered. Because the following vehicle was decelerating, it is assumed it was in the closing regime and would be expected to behave according to Equation 6. The new inserted vehicle's speed is estimated based on the empirical relationship demonstrated in Equation 5, where λ = 0.162 (0.795 when using U.S. customary units). The inserted vehicle's speed is then estimated as shown in Equations 15 through 17.

$$v_{n-1} = \max\{v_n + \lambda a_n, 0\} \quad \text{[Eq. 15]}$$

$$v_{n-1} = \max\{15 + 0.162(-1), 0\} \quad \text{[Eq. 16]}$$

$$v_{n-1} = 14.84\text{m/s} \quad \text{[Eq. 17]}$$

The inserted vehicle's position is determined using Equation 9 and is calculated as shown in Equations 18 through 20.

$$\Delta x = ABX - \frac{1}{2} \cdot \frac{(\min\{-\lambda a_n, v_n\})^2}{a_n} \quad \text{[Eq. 18]}$$

$$\Delta x = 7.25 + 2.5\sqrt{15} - \frac{1}{2} \cdot \frac{(\min\{-0.162(-1), 15\})^2}{-1} \quad \text{[Eq. 19]}$$

$$\Delta x = 18.24 \text{ m} \quad \text{[Eq. 20]}$$

The new vehicle is inserted into the algorithm at the estimated speed, location, and acceleration as shown in Figure 6 and continues to drive according to the Wiedemann model until an EV overlaps it or it leaves the network, at which point it is deleted. A vehicle inserted at time t must survive the analysis at time t+1 before it is considered in the results.

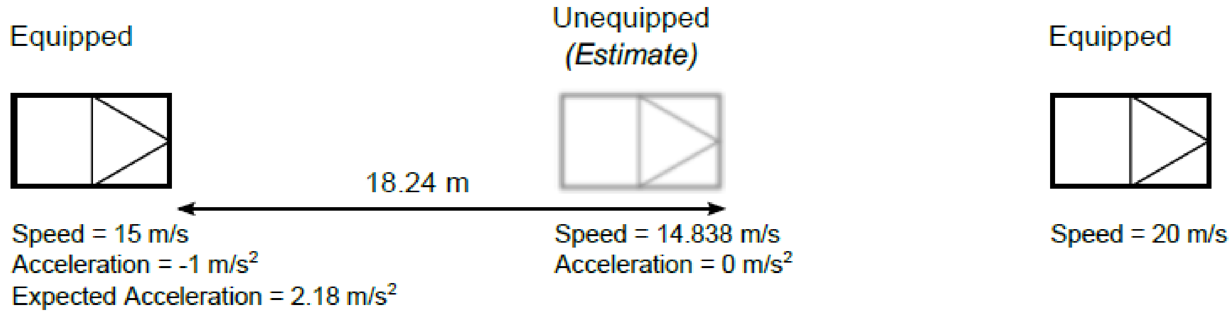

Figure 6. Example of Freeway Location Estimation Algorithm After Estimate of a Vehicle's Location and Speed Were Inserted Into Network

Task 3: Development of Testing Parameters for Developed Algorithms

The location estimation algorithms were tested in simulation and against empirical vehicle trajectory datasets. Several performance metrics were tested, including the following:

- *Freeways*
  - effective penetration rate
  - density visualizations
  - inserted vehicle lifespan
  - improvements in stops, delay, speed, and distance traveled when the algorithm is applied to a connected vehicle ramp metering algorithm at various EV penetration rates.
- *Arterials*
  - effective penetration rate
  - mean absolute error (MAE) of estimated versus actual queue length
  - MAE of estimated versus actual number of queued vehicles
  - improvements in stops, delay, speed, and stopped delay when the algorithm is applied to a connected vehicle traffic signal control algorithm at various EV penetration rates.

Only one of these metrics, the effective penetration rate, is unique to this study. It is described in the following sections. The other metrics are described as they are introduced in the Task 4 results section.

Effective Penetration Rate

The arterial analysis focused on queue length, which is an important metric for signal timing applications. However, queue length measures only stopped vehicles. Equally important are the moving vehicles approaching the intersection, particularly groups of vehicles moving together along a signalized corridor, called platoons. A new metric is needed to measure the ability of the arterial location estimation algorithm to estimate the locations of both moving and queued vehicles.

General Example

Measuring the performance of the location estimation algorithms is challenging. Normally the difference between observed and estimated values can be measured and averaged, which requires a one-to-one relationship between estimates and observations. The location estimation algorithms, by contrast, often have a different number of estimates (inserted vehicles) and observations (unequipped vehicles). A new metric was developed to provide some understanding of the performance of the algorithms and is referred to as the effective penetration rate, PR_{eff}. The effective penetration rate metric is essentially the number of EVs, plus the number of "correct" inserted vehicles, minus the number of "incorrect" inserted vehicles, divided by the total number of equipped and unequipped vehicles, as shown in Equation 21.

$$\mathrm{PR}_{\mathrm{eff}} = \frac{\text{No. Equipped Vehicles} + \text{No. Correct Insertions - No. Incorrect Insertions}}{\text{No. Equipped Vehicles} + \text{No. Unequipped Vehicles}} \qquad \text{[Eq. 21]}$$

For example, an application of 70 EVs and 30 unequipped vehicles can be considered. The penetration rate is 70/(30 + 70) = 70%. There are also 15 inserted vehicles. Ten of the inserted vehicles are within the same lane and within range of unique unequipped vehicle and are considered correct estimates. Five are not within range of unique unequipped vehicles and are considered incorrect estimates. The effective penetration rate would be calculated as (70 + 10 - 5)/(70 + 30) = 75%. Thus, the effective penetration rate has a maximum value of 100%.

Specific Formulation

The previous calculation is a high-level example for a single lane at a single second. To calculate the effective penetration rate for the entire network over a period of time, the following procedure should be used.

1. Sort the individual estimates and observations within the same lane and time into exclusive pairs based on the nearest neighbor. Only one observation for any time and lane may be matched with a single estimation at the same time and lane and vice versa.

2. Record the one-dimensional distance between these two values as the minimum absolute distance between any single estimated location and observed location.

This procedure is defined in the iterative process, performed from n = 1 to $\#O_{t,l}$, as described in Equations 22 through 26.

$$X_{t,l}(n) = \begin{cases} \min\left\{\left(O_{t,l} \times E_{t,l}\right)_i - \left(O_{t,l} \times E_{t,l}\right)_j\right\} & \text{if } n \leq \#O_{t,l} \\ \infty & \text{if } n > \#O_{t,l} \end{cases} \qquad \text{[Eq. 22]}$$

$$A = \left\{O_{t,l} \notin O_{t,l}(i)\right\} \qquad \text{[Eq. 23]}$$

$$O_{t,l} = A \qquad \text{[Eq. 24]}$$

$$B = \left\{E_{t,l} \notin E_{t,l}(j)\right\} \qquad \text{[Eq. 25]}$$

$$E_{t,l} = B \qquad \text{[Eq. 26]}$$

where

O = set of all observations
X = set of errors for each vehicle location estimation in the set E
E = set of all vehicle location estimates
l = individual lanes in the set of all lanes L
L = set of all lanes
t = individual time intervals in the set of all time intervals T
T = set of all time intervals
= symbol specifying the number of elements in the identified set
i = observation with the lowest error for iteration n
j = estimation with the lowest error for iteration n
A, B = placeholders.

In each iteration n, the variables i and j represent the minimum respective observation and estimation with the closest relative error of the set, as shown in Equation 22. These individual records are removed from the set in Equations 23 through 26, using sets A and B as placeholders.

To calculate the effective penetration rate, each location estimation error in X that is less than or equal to the distance ρ is classified as a correct measurement and each greater than ρ is classified as an incorrect measurement. The metric essentially defines all EVs as correct measurements and ensures that any single incorrect measurement cancels out a single correct measurement. The effective penetration rate for a given accuracy distance ρ is defined in Equation 27.

$$\mathrm{PR}_{\mathrm{eff},\rho} = \#S + \frac{2\#\{x \in X : x < \rho\} - \#E}{\#O} \qquad \text{[Eq. 27]}$$

Testing Environment

The arterial location estimation algorithm was tested on a calibrated model of U.S. 50, a four-signal arterial network in Chantilly, Virginia, shown in Figure 7.

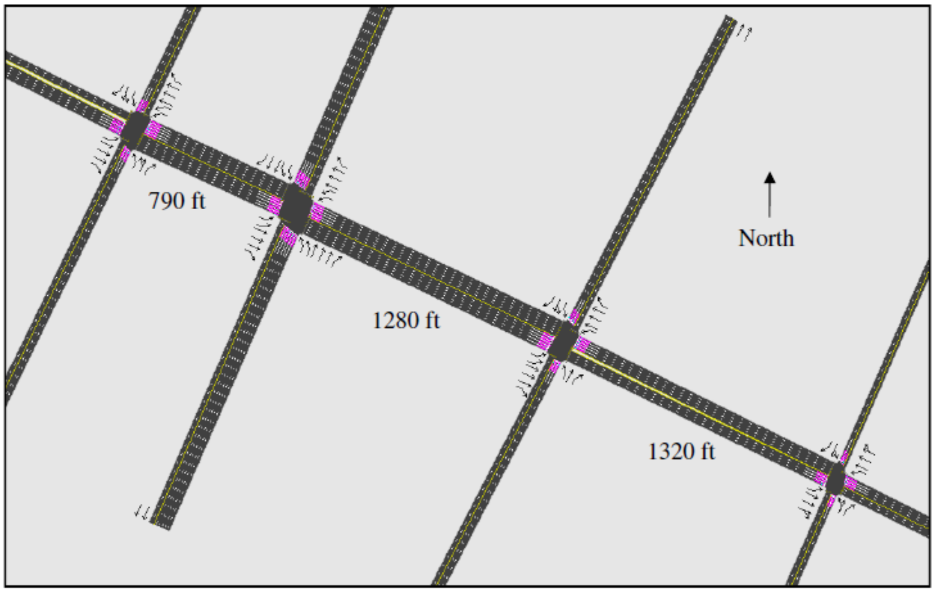

Figure 7. The Arterial Test Network, a 4-Signal Section of U.S. 50 in Chantilly, Virginia

Vehicle volumes and turning movements were collected in 2003 between 3 P.M. and 4 P.M. on weekdays (Park and Schneeberger, 2003). Pedestrian movements, which were very low at these intersections, were ignored in this analysis. The arterial location estimation algorithm was replicated 5 times in each testing scenario. VISSIM was used to simulate vehicle movements (PTV AG, 2011). The arterial location estimation algorithm was tested at EV penetration rates of 5%, 10%, 15%, 25%, 50%, and 100%. The use of VISSIM is somewhat of a best case scenario, as VISSIM's car-following model is based on the Wiedemann model used in the arterial location estimation algorithm.

The arterial location estimation algorithm requires that inserted vehicles decide which way to turn at downstream intersections. The following two methods are used to predict turning decisions:

1. *Default (dflt).* Vehicles are assigned a default 10% probability of turning left, a 10% probability of turning right, and an 80% probability of traveling straight through an intersection. This method was developed to avoid storing records of vehicle movements in a field deployment, either individually or aggregated. Turning movements are considered aggregated vehicle movements.

2. *Measured (msrd).* Vehicles are assigned a probability of turning based on actual turning percentages measured in the field. This requires the recording of aggregated vehicle movements during a field deployment, which may impact privacy.

The same network was used to test the connected vehicle traffic signal control application, described in the Task 4 results section.

As discussed previously, the freeway location estimation algorithm was tested using vehicle trajectory data from the NGSIM project, a field-collected dataset of vehicle movements along several corridors in the United States (FHWA, 2010). Vehicle movements were collected from video recordings and then extracted via specialized software. A dataset collected from a 500-meter (1,640-foot) section of I-80 in Emeryville, California, between 5:00 P.M. and 5:30 P.M. on April 13, 2005, was used to evaluate the freeway location estimation algorithm. The roadway has five lanes in the northbound direction, along with an on-ramp, off-ramp, and weave area. Only the behavior of vehicles traveling in the through lanes was analyzed; the activity on the ramps and merge lanes was not. Figure 8 shows an overview of the network. Because the NGSIM data list the position of every vehicle 10 times per second, they are considered ground truth data. A portion of vehicles in the dataset were randomly assigned as unequipped vehicles, and their trajectories were removed from the evaluation dataset.

A model of a theoretical ramp metering algorithm was developed to test the connected vehicle ramp metering application. More detailed descriptions of this network and the ramp metering application are provided in the Task 4 results section.

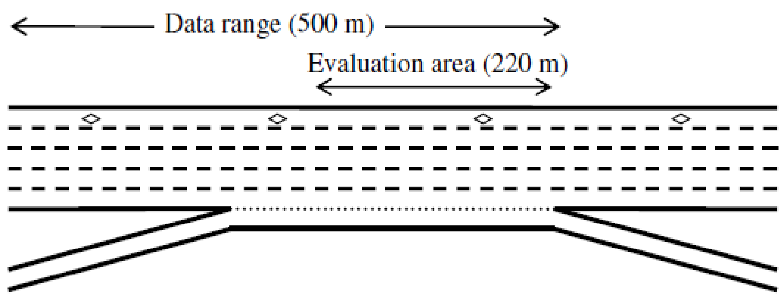

Figure 8. Section of I-80 Used in Next Generation Simulation (NGSIM) Data and Area Evaluated in Study

Task 4: Testing and Evaluation of the Developed Algorithms

Arterial Location Estimation Algorithm

General Performance

Summary statistics of the evaluation of the arterial location estimation algorithm for default and measured turning movements are provided in Table 3. The table uses the following metrics:

- *Number of insertions:* the number of unique instances of inserted vehicles, regardless of how long an inserted vehicle survives. This is roughly equivalent to the number of times an EV triggers an insertion.

- *Number of equipped vehicles:* the number of vehicles with communications capabilities. This is approximately the total number of vehicles in the scenario multiplied by the penetration rate.

Table 3. Summary Statistics of the Evaluation of the Arterial Location Estimation Algorithm

Penetration Rate (%)	5	10	15	25	50	100
Default Turning Movements						
Number of insertions	1,116	1,482	1,963	2,119	2,164	1,568
Number of equipped vehicles	225	449	673	,1126	2,260	4,515
Average inserted vehicle lifespan (s)	74.4	78.9	76.8	72.6	66.4	17.7
Insertions per real vehicle	0.248	0.330	0.438	0.470	0.479	0.347
Insertions per equipped vehicle	4.96	3.30	2.92	1.89	0.96	0.35
Equipped vehicle-seconds per insertion	33.6	47.3	52.5	78.8	155.8	462.3
Measured Turning Movements						
Number of insertions	1,078	1,393	1,946	2,145	2,190	1,630
Number of equipped vehicles	225	447	670	1,122	2,241	4,504
Average inserted vehicle lifespan (s)	74.0	72.0	79.0	72.8	63.2	17.1
Insertions per real vehicle	0.239	0.312	0.436	0.478	0.489	0.362
Insertions per equipped vehicle	4.78	3.12	2.90	1.91	0.98	0.36
Equipped vehicle-seconds per insertion	34.4	46.0	50.3	76.0	154.9	438.1

- *Average inserted vehicle lifespan (s):* the average time in seconds that an inserted vehicle survives and moves forward before it is either overlapped by an EV and deleted or reaches the end of the network.

- *Insertions per real vehicle:* the total number of unique vehicle insertions divided by the total number of vehicles, equipped and unequipped, in the scenario.

- *Insertions per equipped vehicle:* the total number of unique vehicle insertions divided by the total number of EVs. Each EV triggers an average of this number of insertions during its drive through the network.

- *Equipped vehicle-seconds per insertion:* the average number of vehicles inserted by an EV as it travels through the network.

As expected, there was very little difference between the default and measured turning movements, as the metrics in Table 3 have to do mostly with the number and initial placement of inserted vehicles rather than their later turning decisions. Inserted vehicles typically remain in the simulation for 70 to 80 seconds unless the EV penetration rate is 100%, at which point inserted vehicles remain for only 17.7 seconds on average.

The 100% penetration rate scenario was included because in a field deployment there may be no way to measure the actual penetration rate at any given time. The arterial location estimation algorithm may be inadvertently used even with high penetration rates, and it is useful to know if the algorithm produces significant errors with high penetration rates. Ideally, at high penetration rates, the algorithm would not be activated.

Figure 9 shows a sample of vehicle trajectories of equipped, unequipped, and inserted vehicles in the network at a 15% EV penetration rate. Ideally, each inserted vehicle will match the trajectory of a unique unequipped vehicle. Of particular note are the insertion of several vehicles in a stopped queue and the arrival of several vehicles inserted downstream of the subject intersection.

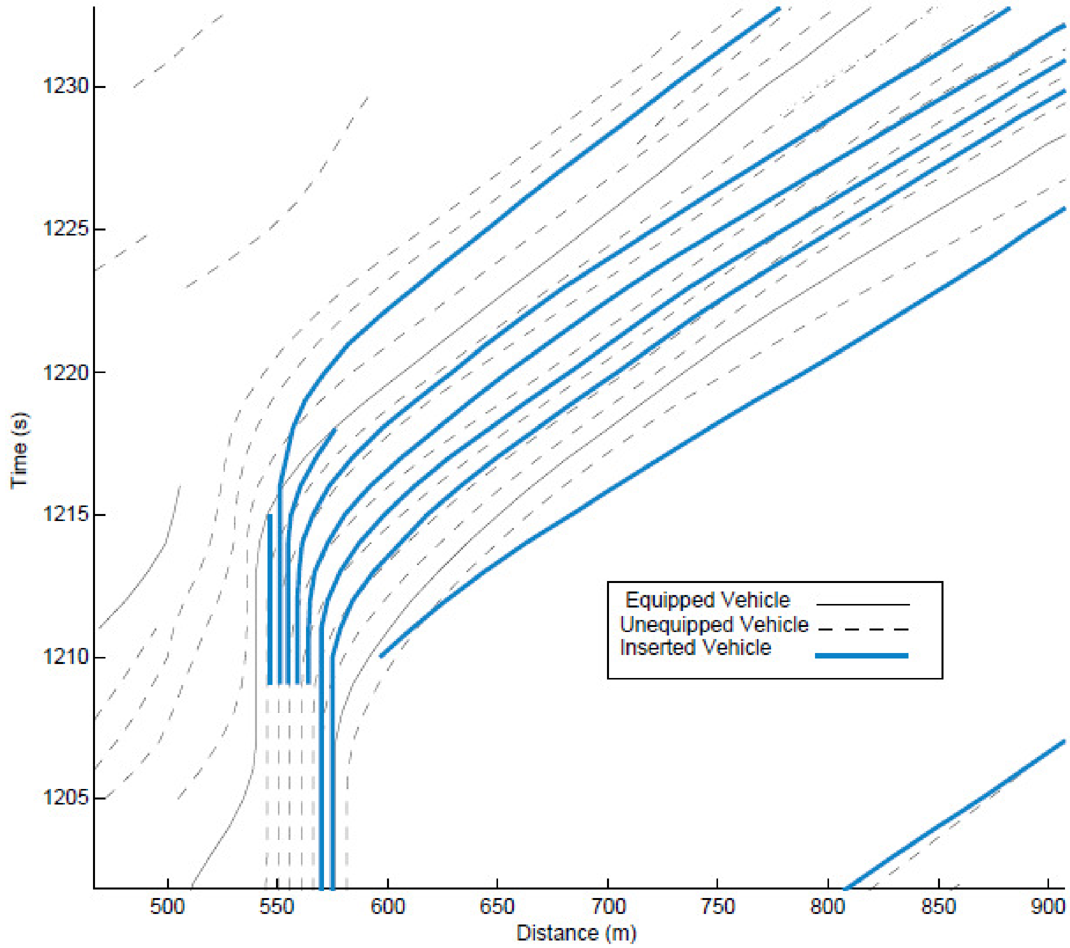

Figure 9. Sample of Vehicle Trajectories of Equipped, Unequipped, and Inserted (Estimated) Vehicles at 15% Equipped Vehicle Penetration Rate on Single Lane

Queue Length and Queued Vehicle Count

An important factor in signal timing decisions is the queue length at an intersection in terms of both distance and number of queued vehicles. In this analysis, queues were measured during the last second of a red phase immediately before a green phase. This represents the largest queues during any particular cycle. The measures of effectiveness used for this evaluation were the MAEs of queue length and number of queued vehicles. MAE is defined in Equation 28.

$$MAE = \frac{1}{n}\sum_{i=1}^{n} | f_i - y_i | \qquad \text{[Eq. 28]}$$

where

f_i = predicted value
y_i = ground truth value.

The MAEs of the queue lengths and number of queued vehicles immediately before green phases are listed in Table 4, and individual measurements are shown graphically in Figure 10. From the table, the arterial location estimation algorithm produces a very small improvement in queue length across all penetration rates. The queued vehicle count is substantially improved when the penetration rate is below 100% but is worse at 100% penetration as the algorithm will insert vehicles to balance queues on multilane approaches.

Table 4. Mean Absolute Error (MAE) of Queue Length and Number of Queued Vehicles Measured for Each Approach Immediately Before Next Green Phase for Arterial Location Estimation Algorithm

	MAE Queue Length (m)			MAE Queued Vehicle Count		
PR (%)	**EV-Only**	**LE-dft**	**LE-msrd**	**EV-Only**	**LE-dft**	**LE-msrd**
5	16.8	16.3	16.4	7.3	6.0	6.0
10	11.6	11.0	11.6	5.8	4.2	4.3
15	9.1	8.6	8.8	5.4	3.3	3.4
25	6.5	6.2	6.0	4.6	2.5	2.4
50	2.9	3.1	2.9	3.3	1.5	1.3
100	0.0	0.1	0.1	0.0	0.9	0.9

Values are averaged across all movements in the network. PR = equipped vehicle penetration rate; EV-only = the measurements from equipped vehicles only; LE-dft = the arterial location estimation algorithm in effect but with default turning movements; LE-msrd = the arterial location estimation algorithm in effect but with field-measured turning movements.

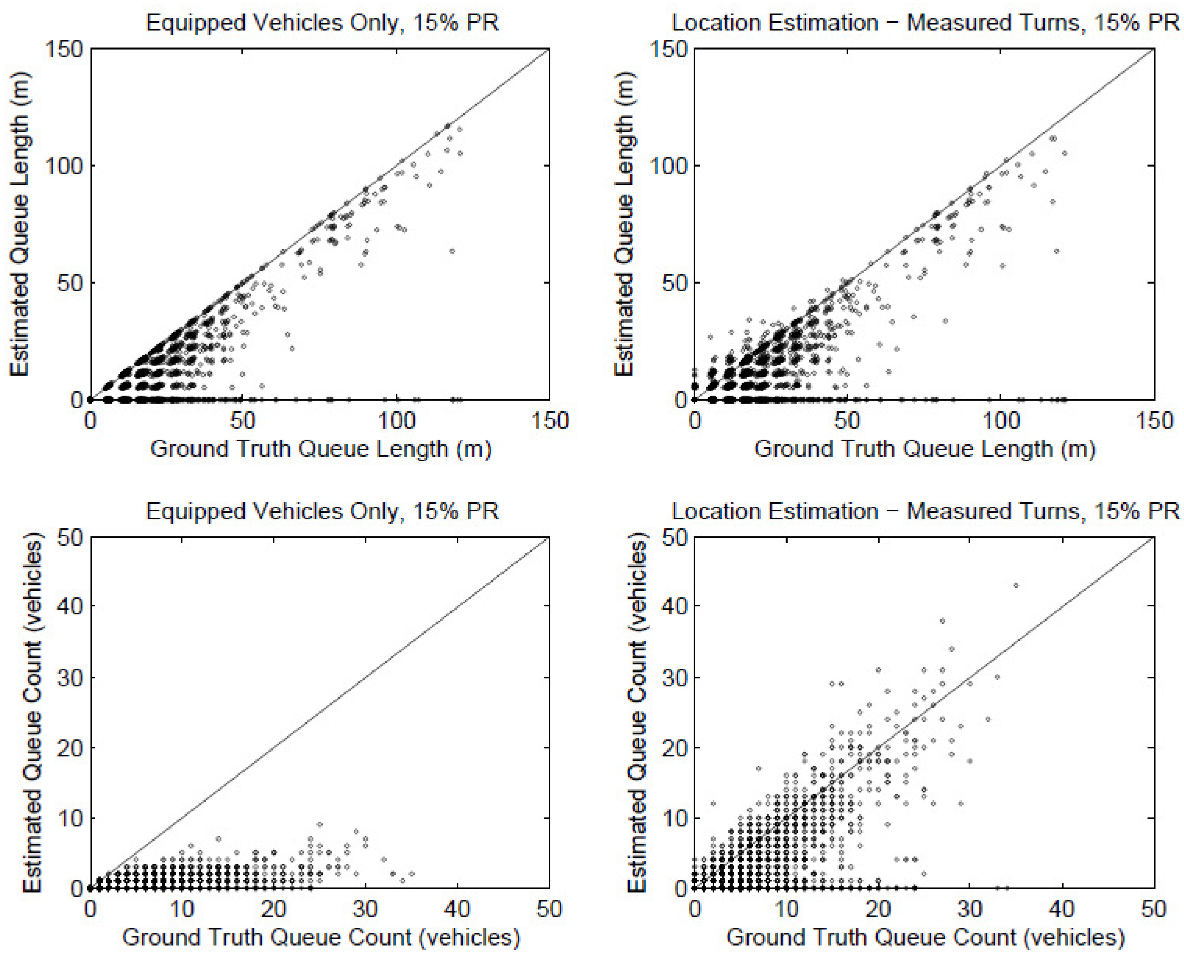

Figure 10. Estimated vs. Actual Queue Lengths and Number of Queued Vehicles at 15% Penetration Rate for Arterial Location Estimation Algorithm

Effective Penetration Rate

The effective penetration rate PR_{eff}, discussed previously, measures the accuracy of the location estimation algorithms. It represents the percentage of all vehicles with "known" locations, including both EVs and unequipped vehicles with a one-to-one relationship with an inserted vehicle within the specified accuracy distance. The effective penetration rate across the entire evaluation network averaged over five runs is shown in Table 5.

In Table 5, values in bold indicate when the effective penetration rate PR_{eff} is higher than the actual penetration rate, i.e., when there are more correct than incorrect estimates. For most penetration rates tested, the algorithm produced more accurate than inaccurate estimates at $\rho > 7$ meters (23 feet). At a 100% penetration rate, every estimate is automatically incorrect and the effective penetration rate is 96.2% regardless of ρ. Although the algorithm should never be used at the 100% penetration rate as it produces only noise, in implementation, the actual percentage of EVs may not be known. In some circumstances, penetration rates may approach 100% while the location algorithm is still running, and therefore it is useful to investigate the error produced by the location estimation algorithm in these circumstances.

Because vehicles are inserted in stopped queues, the effective penetration rate is expected to be higher in the vicinity of a traffic signal. Figure 11 shows the effective penetration rates for several actual penetration rates along the test corridor for eastbound traffic. The vertical dotted lines in Figure 11 represent the stop bar immediately prior to the traffic signal. The minimum estimate accuracy ρ is 10 meters (31 feet) in this example.

Table 5. Effective Penetration Rate Over Entire Test Network Averaged Over 5 Simulation Runs for Arterial Location Estimation Algorithm

Accuracy Distance ρ (m)	**Penetration Rate (%)**					
	5	**10**	**15**	**25**	**50**	**100**
1	-3.3	-2.5	-0.9	9.8	36.9	96.2
2	-0.6	1.4	4.1	14.3	40.8	96.2
3	1.3	4.2	7.6	17.6	43.4	96.2
4	2.7	6.2	10.1	20.0	45.3	96.2
5	3.8	8.0	12.4	22.1	46.9	96.2
6	4.9	9.6	14.4	24.0	48.4	96.2
7	**5.8**	**11.0**	**16.2**	**25.6**	49.7	96.2
8	**6.6**	**12.2**	**17.8**	**27.1**	**50.8**	96.2
9	**7.3**	**13.3**	**19.2**	**28.4**	**51.9**	96.2
10	**7.9**	**14.3**	**20.4**	**29.5**	**52.7**	96.2
11	**8.4**	**15.1**	**21.4**	**30.4**	**53.5**	96.2
12	**8.8**	**15.7**	**22.2**	**31.3**	**54.2**	96.2
13	**9.3**	**16.4**	**23.0**	**32.0**	**54.8**	96.2
14	**9.6**	**16.9**	**23.6**	**32.7**	**55.4**	96.2
15	**9.9**	**17.5**	**24.3**	**33.3**	**55.8**	96.2

Values in bold indicate when the effective penetration rate PR_{eff} is higher than the actual penetration rate, i.e., when there are more correct than incorrect estimates. At a required accuracy distance ρ of 7 meters (23 feet), the algorithm is able to improve its original penetration rate.

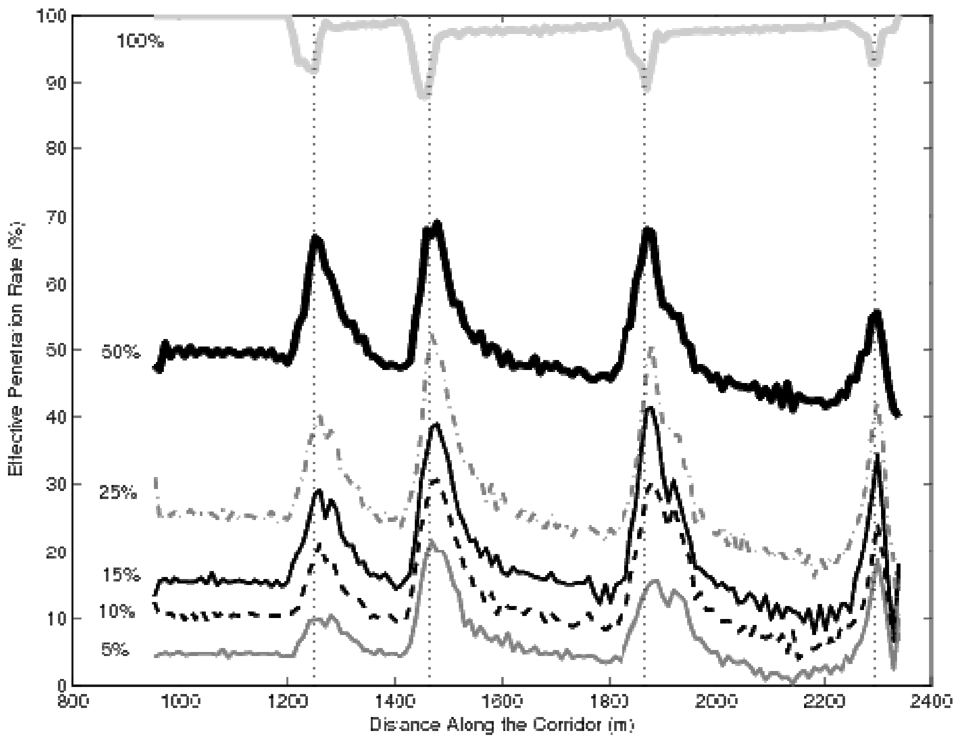

Figure 11. Effective Penetration Rates At Different Points Along Corridor for Eastbound Traffic for Arterial Location Estimation Algorithm. The *vertical dotted lines* represent signalized intersections. The minimum estimate accuracy is 10 meters (33 feet).

As expected, the effective penetration rate is highest near the signal where estimated vehicles are inserted into the queue. The effective penetration rate drops to roughly the previous penetration rate levels approximately 150 meters (492 feet) downstream of the intersection. One possible cause of this drop is the platoon dispersion. When vehicles are no longer clustered in a queue, the minimum required estimate accuracy ρ, which is a distance rather than a headway time, is much harder to maintain. Therefore, the increased effective penetration rates near signals may be partially due to lower vehicle speeds at these locations.

Downstream of the signals, the effective penetration rate continues to decrease, suggesting that over corridors with widely spaced signals, the arterial location estimation algorithm may not be effective if the connected vehicle application requires small minimum estimate errors.

Traffic Signal Control Application

The ultimate objective of the arterial location estimation algorithm is to improve the performance of arterial-based connected vehicle mobility applications. Because these applications perform better at higher EV penetration rates, the research question is whether an estimate of individual unequipped vehicle locations can artificially augment the actual penetration rate and improve performance. To answer this question, the arterial location estimation algorithm was applied to the Predictive Microscopic Simulation Algorithm (PMSA) (Goodall, 2013).

The PMSA is a traffic signal control algorithm that observes individual vehicle locations and predicts their behavior over a 15-second horizon using a commercial traffic simulation software package. The movements over the horizon are repeated for several possible signal phase configurations, and the scenario with the optimized objective function (in this case, minimized delay) is selected as the next phase. This process is repeated continuously. Previous testing of the PMSA in simulation has shown that higher EV penetration rates improve the PMSA's performance and that the PMSA begins to outperform a coordinated-actuated control system at between a 10% and 25% penetration rate.

Evaluation Design

The specific techniques used to operate the model were complex and merit further discussion. The evaluation of the PMSA using arterial location estimation had three parts:

1. ground truth simulation, representing the "real world"

2. rolling estimates of unequipped vehicle locations (i.e., the arterial location estimation component)

3. traffic signal control rolling horizon prediction space where different signal phasings are tested (i.e., the PMSA component).

Each component of the simulation must be operated in a separate simulation instance, with each of the three simulations pausing and restarting while waiting for the calculations from the other simulations. VISSIM was used to control all three simulation components, as VISSIM's Application Programming Interface (API) and COM (Component Object Model) Interface allow users to open, close, run, and pause up to four separate instances of VISSIM simultaneously (PTV AG, 2011).

Figure 12 describes the flow of information among the three simulation instances. In the evaluation, the first simulation window simulates vehicles in the real world. Each second of the simulation, the second simulation instance (i.e., window) will poll the EVs in the first simulation and insert copies of these vehicles into the second simulation. The arterial location estimation algorithm runs in this second simulation, determining gaps in the queue and inserting and deleting unequipped vehicle estimates as needed. When the PMSA determines that a signal should reevaluate its phasing, the third simulation will poll all vehicles in the location estimation simulation and then populate the PMSA simulation with copies.

The PMSA was evaluated in simulation on a model of a four-signal arterial using the field-collected volumes and turning movements (Park and Schneeberger, 2003). Under the tested volumes, the network has an average intersection capacity utilization of 0.75, which is a metric used by the traffic signal timing software Synchro as a surrogate for volume-capacity ratio (Husch and Albeck, 2003). EV penetration rates of 5%, 10%, 15%, 25%, 50%, and 100% were tested 5 times each for 30 minutes with 400 seconds of warm up. In addition, both inserted vehicle turning strategies were tested: (1) the default turning movements where inserted vehicles at all intersections have a 10% probability of turning left and a 10% probability of turning right,

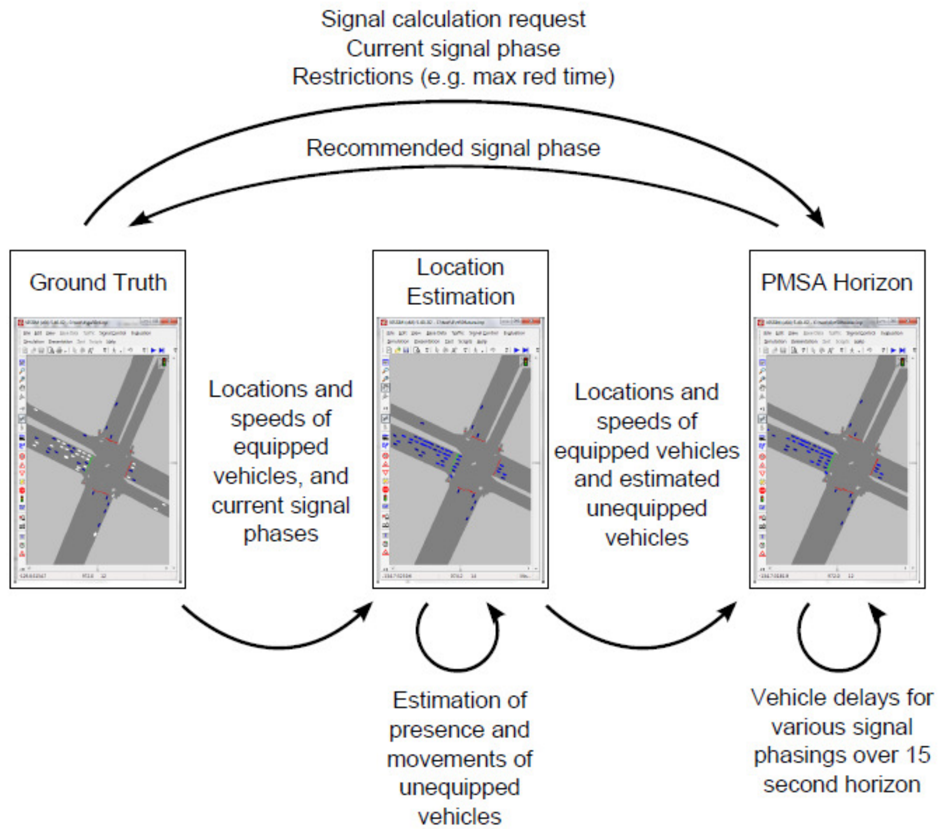

Figure 12. Flow of Information Among the Three Components (Real World or Ground Truth, Arterial Location Estimation, and PMSA) of Traffic Signal Control Application Using Location Estimation

and (2) the field-measured turning movements where a vehicle's probability of turning is equivalent to measured turning probabilities specific to the approach.

Table 6 shows the performance of the arterial location estimation algorithm (using the default and measured turning movements) when compared to the PMSA using EVs only. *P*-values represent the results of a two-tailed *t*-test assuming unequal variances. The same data are shown graphically in Figure 13.

Performance Compared to Equipped Vehicle–Only Scenario

Both location estimation algorithms are able to improve the performance of the PMSA significantly during certain situations. Improvements were found in delay, speed, and stopped delay when the penetration rate was 25% or less. Improvements in stops at these penetration rates were very small or nonexistent. The improvements in delay, speed, and stopped delay were significant ($P < 0.05$) only for the two-tailed two-sample *t*-test assuming unequal variances) at 10% and 25% penetration rates. *P*-values were less than 0.3% at a 15% penetration rate.

The arterial location estimation algorithm substantially worsened the performance of the PMSA at higher penetration rates of 50% and 100%, with up to 14% increases in stops at a 100% penetration rate. This may be due to the poor performance of the PMSA at high volumes where low-volume side streets are rarely assigned green unless they reach 120 seconds of red time

Table 6. Performance of PMSA With and Without the Arterial Location Estimation Algorithm

PR (%)	Technique	Delay (s)	EV Diff	*P*-value	LE-dft Diff	*P*-value
5	EV-only	62.6				
	LE-dft	61.7	-1.37%	0.713		
	LE-msrd	61.5	-1.76%	0.327	-0.40%	0.918
10	EV-only	54.1				
	LE-dft	52.7	-2.64%	0.164		
	LE-msrd	51.6	-4.71%	0.040	-2.13%	0.343
15	EV-only	50.0				
	LE-dft	49.1	-1.78%	0.310		
	LE-msrd	48.3	-3.38%	0.280	-1.63%	0.598
25	EV-only	47.1				
	LE-dft	45.2	-4.04%	0.015		
	LE-msrd	45.0	-4.41%	0.025	-0.38%	0.835
50	EV-only	45.2				
	LE-dft	46.4	2.66%	0.057		
	LE-msrd	46.6	3.12%	0.015	0.45%	0.633
100	EV-only	48.3				
	LE-dft	52.8	9.32%	0.000		
	LE-msrd	52.9	9.39%	0.013	0.06%	0.981

PR (%)	Technique	Speed (mi/hr)	EV Diff	*P*-value	LE-dft Diff	*P*-value
5	EV-only	26.6				
	LE-dft	26.8	0.82%	0.588		
	LE-msrd	26.8	0.99%	0.252	0.16%	0.918
10	EV-only	28.0				
	LE-dft	28.3	1.19%	0.116		
	LE-msrd	28.5	1.88%	0.037	0.68%	0.424
15	EV-only	28.8				
	LE-dft	29.0	0.90%	0.121		
	LE-msrd	29.2	1.40%	0.162	0.50%	0.587
25	EV-only	29.3				
	LE-dft	29.8	1.57%	0.031		
	LE-msrd	29.8	1.65%	0.003	0.08%	0.898
50	EV-only	29.7				
	LE-dft	29.5	-0.62%	0.130		
	LE-msrd	29.5	-0.63%	0.109	-0.01%	0.987
100	EV-only	29.1				
	LE-dft	28.2	-2.81%	0.000		
	LE-msrd	28.2	-2.87%	0.007	-0.06%	0.937

PR (%)	Technique	Stopped Delay (s)	EV Diff	*P*-value	LE-dft Diff	*P*-value
5	EV-only	37.1				
	LE-dft	35.4	-4.56%	0.409		
	LE-msrd	35.5	-4.32%	0.235	0.26%	0.967
10	EV-only	29.6				
	LE-dft	27.6	-6.80%	0.042		
	LE-msrd	27.4	-7.64%	0.033	-0.91%	0.807
15	EV-only	26.2				
	LE-dft	25.3	-3.21%	0.214		
	LE-msrd	24.8	-5.14%	0.263	-2.00%	0.665
25	EV-only	24.5				
	LE-dft	22.6	-8.04%	0.000		
	LE-msrd	22.5	-8.20%	0.008	-0.17%	0.945
50	EV-only	23.9				
	LE-dft	24.0	0.15%	0.950		
	LE-msrd	23.8	-0.58%	0.713	-0.73%	0.719
100	EV-only	26.4				
	LE-dft	28.5	7.67%	0.063		
	LE-msrd	28.8	9.11%	0.015	1.33%	0.719

PR (%)	Technique	Stops	EV Diff	*P*-value	LE-dft Diff	*P*-value
5	EV-only	6223				
	LE-dft	6493	4.33%	0.255		
	LE-msrd	6437	3.44%	0.232	-0.85%	0.824
10	EV-only	5707				
	LE-dft	5727	0.36%	0.883		
	LE-msrd	5633	-1.30%	0.474	-1.65%	0.476
15	EV-only	5349				
	LE-dft	5397	0.91%	0.624		
	LE-msrd	5278	-1.32%	0.675	-2.21%	0.480
25	EV-only	4997				
	LE-dft	4997	-0.02%	0.993		
	LE-msrd	4973	-0.48%	0.800	-0.47%	0.819
50	EV-only	4680				
	LE-dft	4967	6.12%	0.050		
	LE-msrd	4961	6.01%	0.002	-0.10%	0.964
100	EV-only	4843				
	LE-dft	5521	13.98%	0.000		
	LE-msrd	5457	12.68%	0.073	-1.14%	0.825

PR = equipped vehicle penetration rate; EV-only = equipped vehicles only; LE-dft = location estimation algorithm using default turning movements; LE-msrd = location estimation algorithm using measured turning movements; EV Diff = percent difference from EV-only results; LE-dft Diff = percent difference from LE-dft results; *P*-values represent the results of a two-tailed t-test assuming unequal variances.

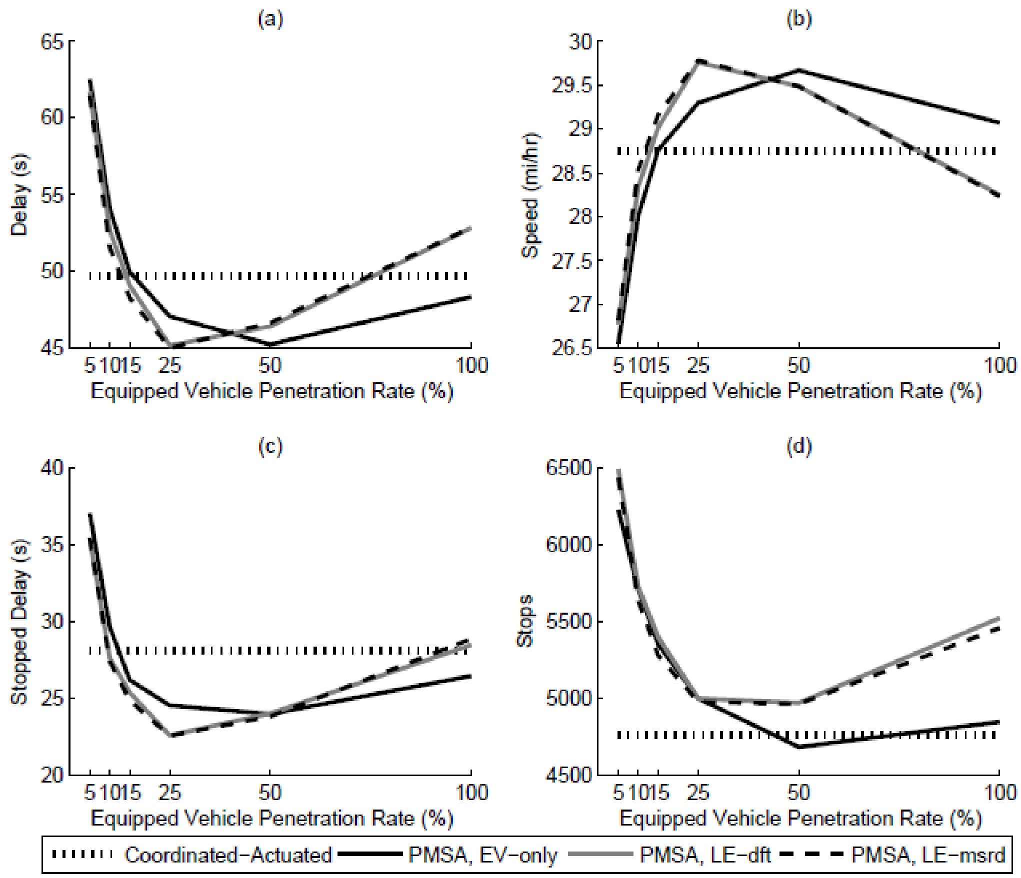

Figure 13. Performance of PMSA Using Equipped Vehicle Locations Only (EV-only), Supplemented With the Location Estimation Algorithm Using Default Turning Movements (LE-dft), and Field-Measured Turning Movements (LE-msrd) As Compared to Coordinated-Actuated Timing Plan. Measures of effectiveness were (a) average delay, (b) average speed, (c) average stopped delay, and (d) total number of stops. The location estimation algorithms were not statistically different. Both performed better than the EV-only scenario at a penetration rate between 15% and 25% but worsened performance at penetration rates of 50% and higher.

(Goodall, 2013). When this occurs, the PMSA is essentially acting with an uncoordinated fixed time plan, which although effective at isolated intersections, fails to react to the platoon arrivals in a signalized corridor. The arterial location estimation algorithm, by estimating more vehicles than are actually present when used at high penetration rates, may encourage this effect. In any event, the evidence suggests that the arterial location estimation algorithm should not be used at penetration rates of 50% and higher.

Performance of Default vs. Measured Turning Volumes

Two versions of the arterial location estimation algorithm were tested. The first used the default static turning percentage to assign probabilities that inserted vehicles will turn at downstream intersections. The default percentages were 10% probability of turning right, 10% probability of turning left, and 80% probability of traveling straight through. Default turning probabilities were tested so that the PMSA could employ the arterial location estimation algorithm while still adhering to its fourth objective to protect driver privacy by avoiding the collection of vehicle trajectories over time, whether aggregated or individualized. Turning movements were considered aggregated vehicle trajectories. The second version of the arterial location estimation algorithm used the field-measured turning percentages to assign probabilities.

As may be seen from Table 6 and Figure 13, the differences between measured and default turning percentages were statistically insignificant. It is worth noting that although the significance was small ($P > 0.34$ in all cases), the measured turning movements outperformed the default turning movements in all measures of effectiveness when the penetration rate was 25% or smaller. It is possible that the benefits of measured turning movements were small because of the characteristics of the test network. In the model of U.S. 50 used in the evaluation, there were few lanes with shared turns (i.e., through and left or through and right combined lanes), and the few that had them had very low volumes. Most vehicles inserted into a queue had only one choice of where to turn, and the turning movement decisions affected their decisions only at downstream intersections. On a network with many shared turn lanes, such as an urban network, the turning decision becomes much more important. On these networks, the measured turning movements would likely outperform the default turning movements, although more research would be needed for certainty.

Freeway Evaluation

As discussed previously, the freeway location estimation algorithm was tested using vehicle trajectory data from the NGSIM project, a field-collected dataset of vehicle movements along several corridors in the United States (FHWA, 2010). A portion of vehicles in the dataset were randomly assigned as unequipped vehicles, and their trajectories were removed from the evaluation dataset.

Table 7 shows summary statistics from the I-80 simulation using the freeway location estimation algorithm. The table uses the same metrics as in Table 3, defined previously.

The algorithm was tested at various penetration rates between 5% and 100%. Although the algorithm should never be used at the 100% penetration rate as it produces only noise, in implementation the actual percentage of EVs may not be known. In some circumstances, penetration rates may approach 100% while the location algorithm is still running, and therefore it is useful to investigate the error produced by the freeway location estimation algorithm in these circumstances.

In the 100% connected vehicle penetration rate scenario, the number of vehicles inserted was unusually high at 116,820 on a network with a measured volume of only 2,460 vehicles. The number of insertions was higher because there are more EVs able to trigger insertions.

Table 7. Summary Statistics of Evaluation of Freeway Location Estimation Algorithm

Penetration rate (%)	10	25	50	70	100
Number of insertions	6,731	8,459	7,320	88,761	16,820
Number of equipped vehicles	261	634	1,219	1,712	2,460
Average inserted vehicle lifespan (s)	6.63	4.78	3.12	2.30	1.47
Insertions per real vehicle	6.79	15.60	27.31	36.01	47.39
Insertions per equipped vehicle	64.1	60.6	55.2	51.8	47.4
Equipped vehicle-seconds per insertion	1.89	2.13	2.35	2.50	2.72
Total inserted vehicle-seconds	31,622	183,843	210,038	204,150	171,725

Usually, this would dramatically increase the estimated volume of the network. However, the inserted vehicles do not survive very long once inserted, averaging only 1.47 seconds per vehicle before being deleted from the simulation entirely. Across all penetration rates, there were many more inserted vehicles than there were equipped or unequipped vehicles. This does not mean that the algorithm overestimated the number of unequipped vehicles. Rather, the inserted vehicles do not survive very long, averaging between 1 and 7 seconds before deletion. An unequipped vehicle may be "estimated" by several inserted vehicles during the 20 to 60 seconds needed to traverse the study section.

The EVs in the algorithm inserted vehicles at similar rates regardless of the EV penetration rate, with each EV triggering an insertion every 1.89 seconds at a 10% penetration rate and once every 2.72 seconds at a 100% penetration rate. This suggests that vehicles exhibit unexpected behavior quite often in congestion, even when there are no unequipped vehicles to which they can react.

Sensitivity Analysis of Inserted Vehicle Survival Times

The short survival times shown in Table 7 were investigated further. Vehicle insertions that are quickly deleted after overlapping with an EV may indicate that the vehicle was placed in an incorrect position. This could occur for several reasons: the acceleration data for the following vehicle may have been inaccurate or the driver may have deviated from a car-following model, attributable to either sudden braking (vehicles inserted unnecessarily) or inadequate braking (vehicle is inserted too far ahead, and nearby other EVs). Vehicle trajectories from VISSIM represent a best case scenario for the freeway location estimation algorithm, as both are based on the Wiedemann model and therefore should predict similar vehicle movements. The desired speeds and several other inputs used in the freeway location estimation algorithm's calculations were randomized to avoid this similarity. Figure 14 shows the number of vehicles inserted using the freeway location estimation algorithm on the I-80 data at different penetration rates. The 100% penetration rate produced the most short-lived insertions and the fewest long-lived insertions. With lower penetration rates, more inserted vehicles survived for longer periods and produced fewer insertions overall.

The general performance of the algorithm when including estimated vehicles with different lifespans is shown in Figure 15. In this figure, the grayscale represents vehicle densities, with black representing 0 and white representing 20 vehicles. Densities across all lanes of I-80 are shown for each second and 30-meter segment. The top row shows the ground truth densities, and the lower rows show the EV and estimated vehicle densities at different penetration rates and with different inserted vehicle lifespans, e.g., ≥0 seconds, ≥1 second, etc.

As seen in Figure 15, the number of unequipped vehicles was drastically overestimated when all vehicles were included regardless of survival time. Densities appeared much more realistic when only vehicles that had survived at least 1 second were included.

The survival time of an inserted vehicle may be related to the quality of that estimate. In order to measure the quality of an insertion, inserted vehicles were grouped with their respective nearest unequipped vehicle neighbor, similar to the technique used to determine the effective

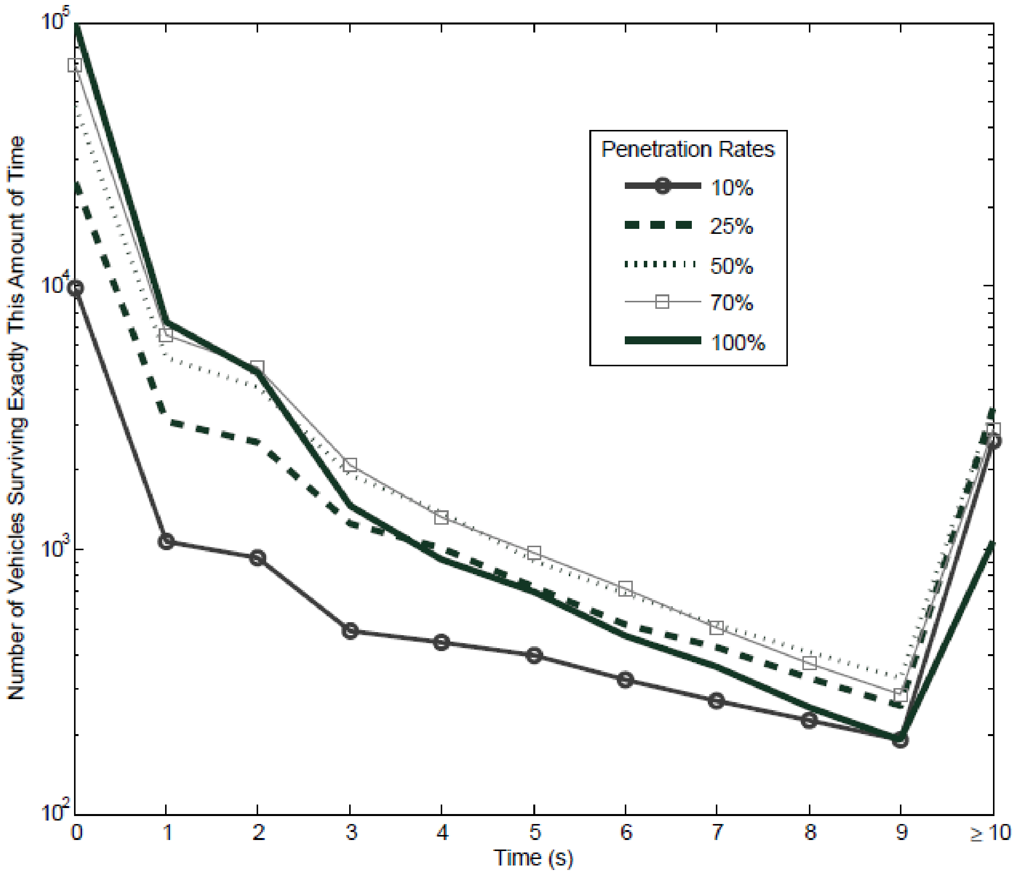

Figure 14. Number of Inserted Vehicles in Using Freeway Location Estimation Algorithm on I-80 Dataset Sorted by Exact Time of Survival in Seconds Across Several Initial Equipped Vehicle Penetration Rates

penetration rate. The distance between a newly inserted vehicle and its nearest unequipped vehicle provides a quantitative measure of the relative accuracy of an insertion. Figure 16 shows the median absolute error of an insertion's initial position using this described method. Some insertions cannot be paired with an unequipped vehicle because there were more insertions than unequipped vehicles. These insertions were ignored in this analysis. This is why the 100% penetration rate was not included in the chart, because there were no unequipped vehicles with which to pair and return distance errors. In Figure 16, the median distance error decreases dramatically when a vehicle survives 0 seconds when compared to vehicles that survive 1 second or longer. A similar effect was found across all penetration rates, and a similar improvement in error was not seen as survival time increased from after 1 second. Based on these findings, only vehicles that survived at least 1 second were considered in the final analyses.

Results After Removing Short-Life Insertions

The remainder of the analysis focused on datasets where any vehicles that survived less than 1 second were removed. This represents the algorithm in its finalized form.

Because the freeway location estimation algorithm requires vehicle interactions to produce any estimates, it requires warm-up time and space. Figure 17 shows estimated vehicle densities for the final 220 meters (722 feet) of the evaluation freeway segment after a 60-second

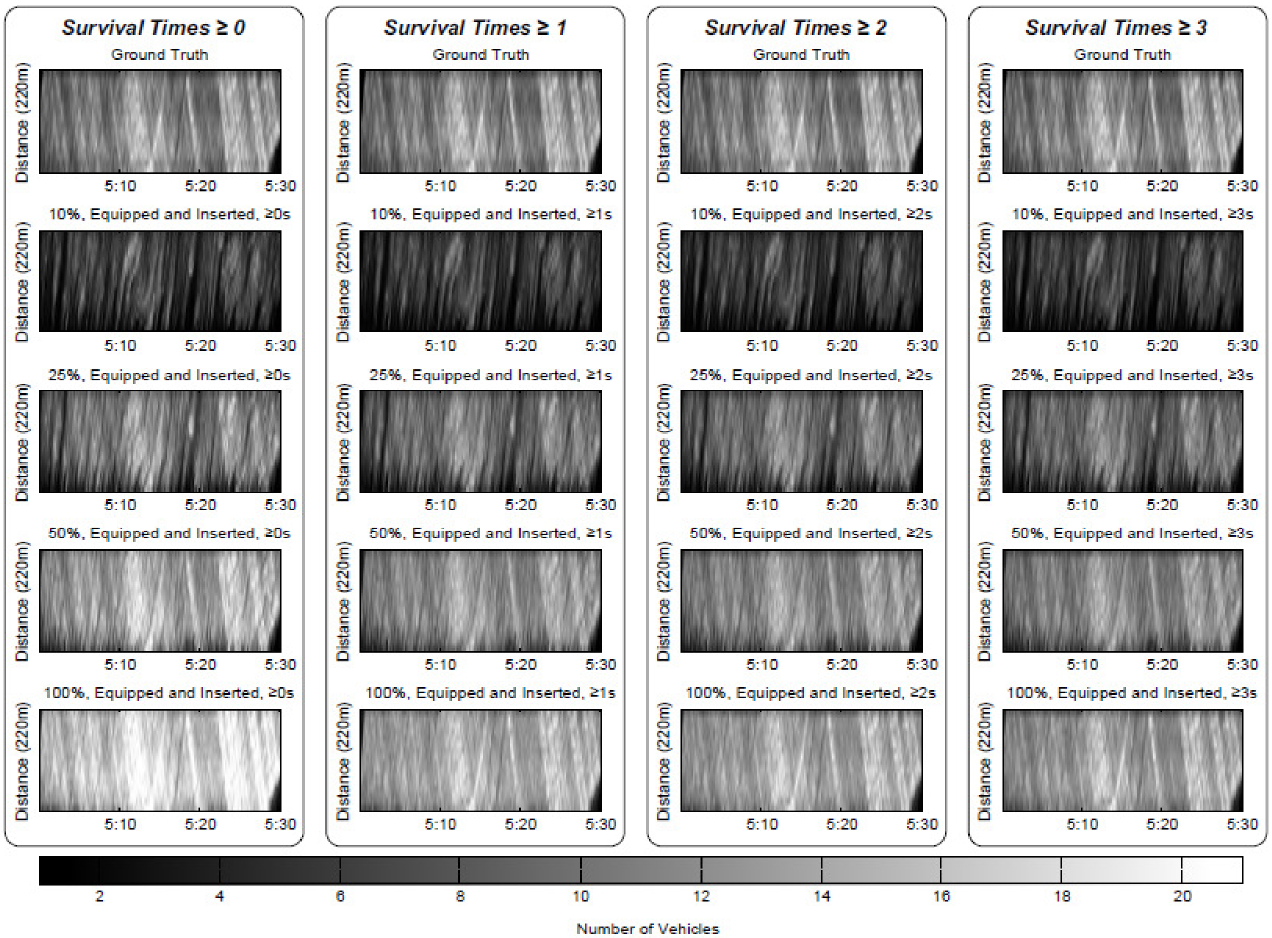

Figure 15. Densities of Estimated and Observed Vehicles at Various Penetration Rates and Survival Times. From left to right, each column represents the densities when vehicles with survival times of ≥0, ≥1, ≥2, and ≥3 seconds, respectively, are included in the counts. Densities are over all lanes, taken each second over 30-meter sections. The grayscale represents vehicle densities, with black representing 0 and white representing 20 vehicles.

initialization at various penetration rates. The left side shows only EVs, and the right shows the densities of both EVs and inserted vehicles. Densities are much more accurate downstream of congestion (vehicles travel bottom to top in Figures 15 and 17) as seen at 25% penetration rates. The algorithm occasionally missed traffic phenomena at low penetration rates, such as the wide moving jam between 5:18 and 5:20, which became visible only at a 50% penetration rate using the freeway location estimation algorithm. At higher penetration rates, because there were so few unequipped vehicles in the network, the algorithm often overestimated densities, as seen at a 100% penetration rate and to a lesser extent at 70% penetration. In spite of its shortcomings, the algorithm provided a substantial improvement over EVs alone at low and medium penetration rates near congestion.

The characteristics of the freeway location estimation algorithm can be demonstrated by analyzing vehicle trajectories. Figure 18 shows the trajectories of equipped, unequipped, and inserted vehicles over a small portion of the I-80 dataset at a 25% penetration rate. In the figure, inserted vehicles are often initially placed near an unequipped vehicle. However, because the

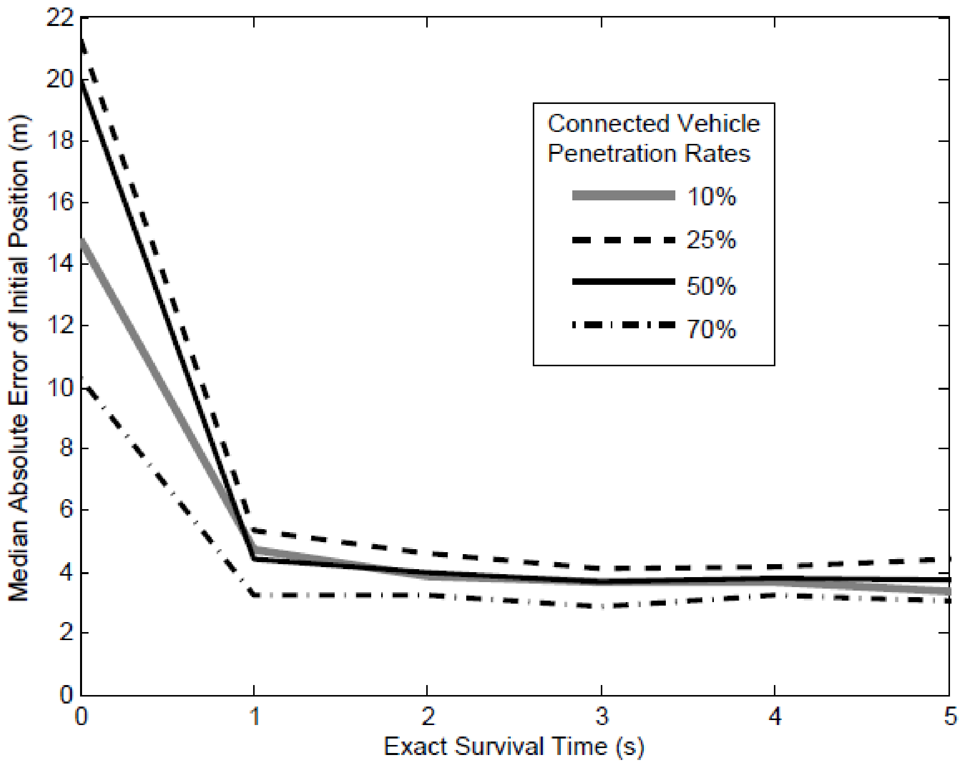

Figure 16. Median Absolute Error of Initial Position of Inserted Vehicles vs. Exact Survival Time of the Vehicles. The error represents the longitudinal distance to the nearest unequipped vehicle in the same lane at the same time, while ensuring a 1-to-1 relationship between inserted and unequipped vehicles, described as the effective penetration rate.

locations of all unequipped vehicles have not been estimated, there is often little traffic nearby with which to interact. As a result, the inserted vehicle accelerates to free flow speed until it encounters an EV or another inserted vehicle. Essentially, the inserted vehicles are "driving" themselves into position. Estimated vehicles are continually inserted behind the original observation and continue to drive themselves into place. This occurs several times in Figure 18 at between 1,140 and 1,160 seconds. As a result, vehicle speeds as estimated by the algorithm are often higher than in actuality, e.g., at a 25% penetration rate, the average speed of estimated vehicles was 27% higher than speeds of observed unequipped vehicles.

Effective Penetration Rate

Table 8 shows the effective penetration rates of the I-80 data at various accuracy distances and actual penetration rates. At very low distances of $\rho \leq 3$ meters, the algorithm generates more incorrect than correct estimates. In addition, at actual penetration rates above 80%, there are few unequipped vehicles to detect and therefore the algorithm performs poorly. The algorithm is most effective at penetration rates of 70% or less with minimum accuracy distances of 5 to 10 meters (16 to 33 feet).

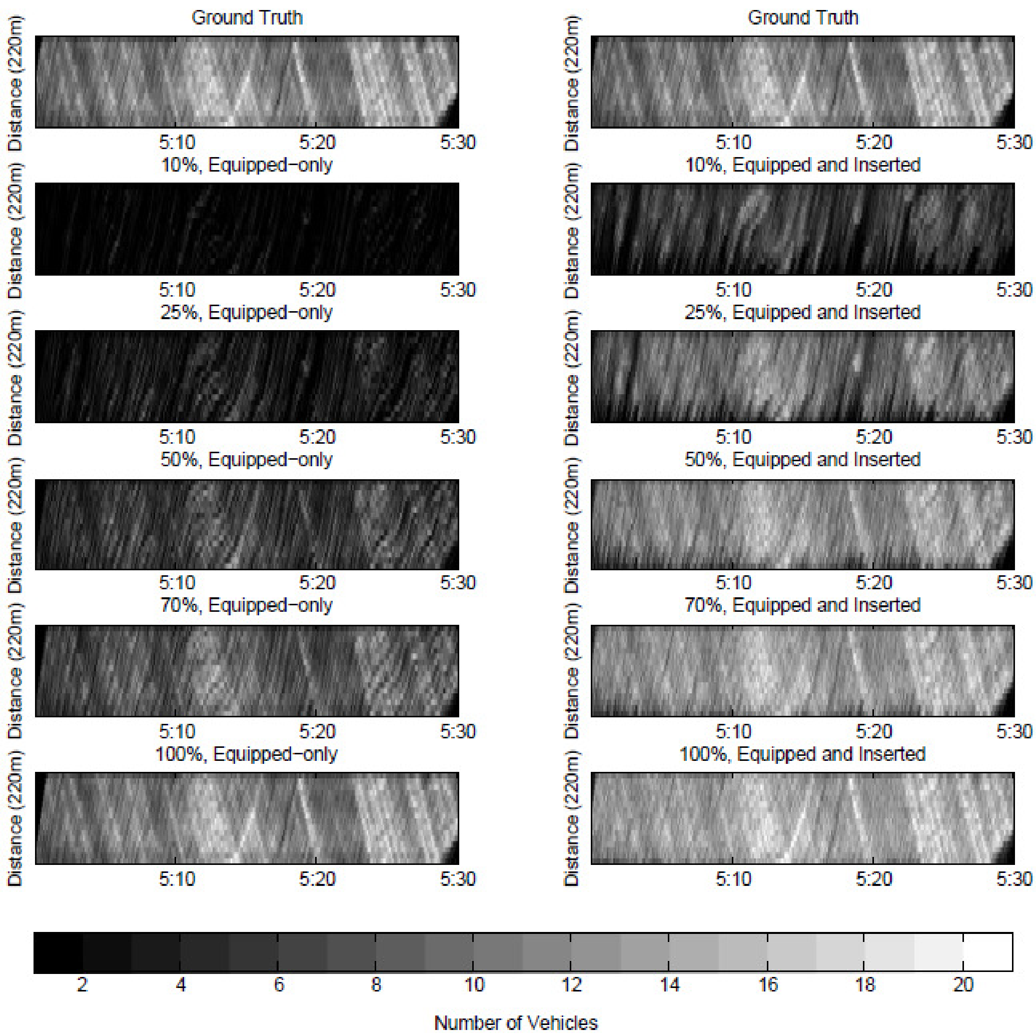

Figure 17. Heat Map of Densities Each Second for 30-Meter (98-Foot) Segments of I-80 at Various Penetration Rates Both With and Without Freeway Location Estimation Algorithm. Accuracy is improved at low penetration rates, but densities are often overestimated at high penetration rates.

Ramp Metering Application

Used alone, the freeway location estimation algorithm is useful for detecting highway conditions and providing an estimate of densities in low- or no-detection segments. However, by providing estimates of individual vehicle locations, the algorithm should also be able to improve the performance of some connected vehicle applications at low penetration rates. To test this theory, the freeway location estimation algorithm was applied to a connected vehicle ramp metering algorithm called the GAP algorithm.

Description of GAP Algorithm

The GAP algorithm is a ramp metering strategy developed by Park (2008). The GAP algorithm analyzes the speeds, accelerations, and locations of mainline vehicles upstream of a freeway on-ramp to predict future gaps in the rightmost lane at the merge area in the near future. On-ramp vehicles receive a green signal by the ramp meter when a gap is predicted on the mainline. If no gap is predicted, the ramp vehicles are held at the signal. Whereas traditional ramp metering algorithms release vehicles at a fixed rate over a set time period, the GAP algorithm releases vehicles at irregular rates based on the prediction of gaps in mainline traffic.

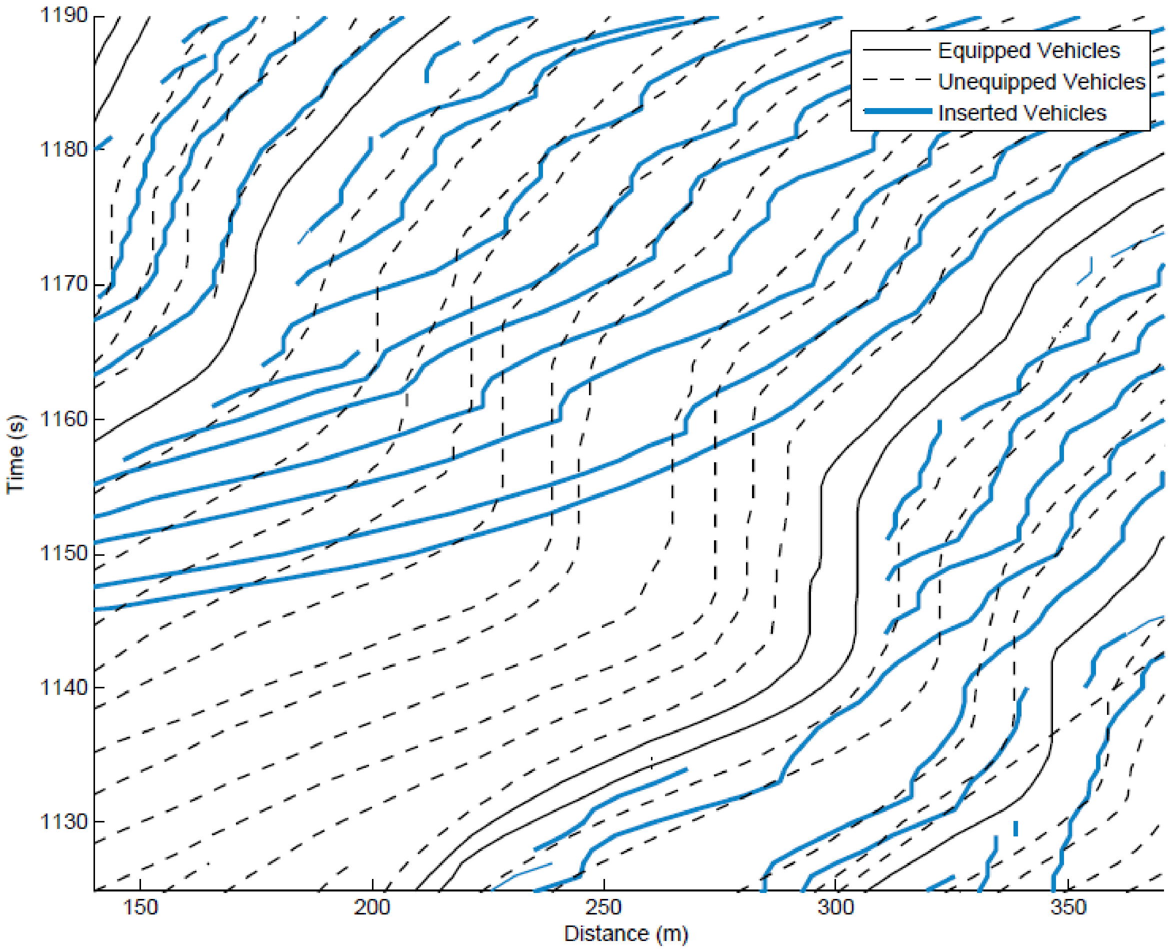

Figure 18. Trajectories of Equipped, Observed Unequipped, and Inserted Vehicles Over Portion of I-80 at 25% Equipped Vehicle Penetration Rate. Estimated vehicles generally have few vehicles with which to interact and therefore drive forward unimpeded, eventually matching an observed vehicle's trajectory. As a result, estimated speeds are often higher than observed speeds at low penetration rates.

Table 8. Effective Penetration Rates of I-80 at Various Accuracies and Actual Penetration Rates

Accuracy	**Penetration Rate (%)**								
Distance ρ (m)	**5**	**10**	**20**	**30**	**40**	**50**	**0**	**70**	**100**
1	-7.5	-1.6	-0.6	-3.0	6.7	8.4	30.1	3.2	83.5
2	-2.8	-3.2	1.3	9.6	18.9	29.3	39.5	50.6	83.5
3	1.8	4.9	12.5	21.3	30.0	39.2	48.0	57.1	83.5
4	*5.9*	*12.2*	*22.4*	*31.5*	39.6	47.6	55.0	62.4	83.5
5	*9.4*	*18.2*	*30.4*	*39.6*	*47.1*	*54.2*	*60.5*	66.7	83.5
6	*12.1*	*22.7*	*36.6*	*45.8*	*52.9*	*59.2*	*64.6*	69.8	83.5
7	*14.1*	*26.2*	*41.1*	*50.4*	*57.2*	*62.8*	*67.7*	*72.1*	83.5
8	*15.6*	*28.6*	*44.4*	*53.8*	*60.3*	*65.5*	*69.9*	*73.8*	83.5
9	*16.7*	*30.5*	*46.9*	*56.3*	*62.6*	*67.4*	*71.5*	*75.1*	83.5
10	*17.5*	*31.8*	*48.7*	*58.0*	*64.3*	*68.9*	*72.7*	*75.9*	83.5

Values in italics indicate improvements over the actual penetration rates.

The GAP algorithm relies on two calculations: the position of the on-ramp vehicle, and the positions of the mainline vehicles. In the implementation tested here, the on-ramp vehicle is expected to follow the Wiedemann car-following model. Upon receiving a green phase, an on-ramp vehicle is expected to hold its current speed for 1 second as the driver reacts to the signal and then accelerate at the rate described in Equation 29.

$$a_t = 3.5 + \frac{3.5}{40} v_{t-1} \qquad \text{[Eq. 29]}$$

where

a_t = acceleration at time t (m/s^2)
v_{t-1} = speed at time t-1 (m/s).

The GAP algorithm then predicts the future positions of vehicles on the mainline in the right lane nearest the on-ramp. Future vehicle positions are predicted using the fundamental equation as shown in Equation 30

$$x_t = x_0 + \frac{1}{2} a_0 t^2 + v_0 t \qquad \text{[Eq. 30]}$$

where

x_t, x_0 = vehicle positions at time t and initial time measurement, respectively.

In the GAP algorithm, at each time step, the vehicle on the on-ramp next in line at the meter has its position projected several time steps into the future.

The positions of vehicles in the mainline's right lane are also projected. If a gap exists at the on-ramp vehicle's projected position before the on-ramp vehicle is projected to reach the end of the merge area, the on-ramp vehicle receives a green signal. If no gap is detected at any of the projected times, the ramp meter is set to red. Vehicle positions are re-calculated each second, and the minimum duration of a green signal is 2 seconds. To prevent backups, the ramp meter is set to green if there are any stopped vehicles on the most upstream 50-meter (164-foot) section of the ramp.

Evaluation of GAP Algorithm With and Without Location Estimation

The test network consisted of a theoretical two-lane freeway with a volume of 4,600 vehicles per hour; a single-lane on-ramp with a volume of 600 vehicles per hour; and an off-ramp with a volume of 200 vehicles per hour. A diagram of the test network is included in Figure 19.

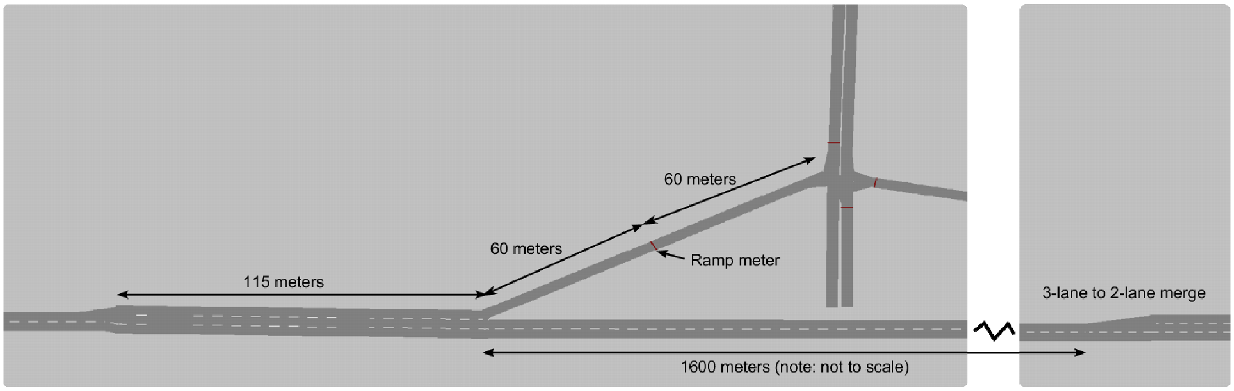

Figure 19. Diagram of Ramp Metering Test Network

As noted previously, the freeway location estimation algorithm is effective only near or downstream of congestion. To generate the necessary congestion on the test network, a three-lane to two-lane merge was placed on the mainline approximately 1 mile upstream of the ramp meter's merge area. This generates the types of vehicle interaction that would occur in many congested freeway networks and is placed far enough upstream that vehicle arrivals at the ramp meter's merge area are not uniform.

The GAP algorithm was originally developed for a 100% EV penetration rate (Park, 2008). In Park's implementation, the GAP algorithm was tested against the fairly sophisticated semi-actuated traffic metering system (SATMS) used in Los Angeles and Orange County, California (Chu et al., 2009). The GAP algorithm was simulated 10 times for each scenario using different random seeds and produced statistically similar performances for each scenario across all metrics, using a *P*-value threshold of 0.10.

Although not evaluated in Park's work, at low EV penetration rates, the freeway location estimation algorithm frequently predicts gaps where there are none, and performance suffers as expected. By use of the freeway location estimation algorithm, the positions of some previously undetected mainline vehicles, i.e., those without the ability to communicate, can be estimated. With better estimations of freeway vehicle positions, the GAP algorithm should theoretically make better gap predictions and therefore improve flow and reduce delay and queues.

The GAP algorithm was tested at connected vehicle penetration rates of 10%, 25%, 50%, 75%, and 100%, both with and without the freeway location estimation algorithm. A fixed time metering strategy designed for the expected flow rate at the ramp of one vehicle every 6 seconds was used as a performance baseline. Table 9 shows the results of the analysis.

The freeway location estimation algorithm demonstrates a statistically significant effect on the performance of the GAP algorithm at low and medium penetration rates. At a 10% penetration rate, the GAP algorithm was able to increase vehicle speed in the merge area distance traveled, with no measurable effect in any other area. The freeway location estimation algorithm's effect was more noticeable at 25% and 50% penetration rates, with several metrics within or near a 10% significance level. As shown from the I-80 analysis, the freeway location estimation algorithm produces more incorrect than correct estimates at high penetration rates, and as expected, no measurable benefit was found at a 75% or 100% penetration rate.

Table 9. Performance of GAP Ramp Metering Algorithm With and Without Freeway Location Estimation Algorithm and Compared Against Fixed Time Metering Strategy

CV Penetration Rate	Vehicle Prediction Algorithm	Delay/ Vehicle (s)	Network Speed (km/h)	Distance Traveled (km)	Number of Stops	Speed Near Merge Area (m/s)
–	Fixed Time Meter	95.5	48.1	8597	7819	17.1
10%	Off	94.0	48.5	8618	7745	15.7
	On	87.7	50.1	8680	7481	17.1
	Difference	-6.6%	3.4%	0.7%	-3.4%	8.4%
	Loc. Est. p-value	0.261	0.108	0.073*	0.352	0.056*
	Fixed Time p-value	0.133	0.126	0.029*	0.222	0.991
25%	Off	94.4	48.3	8605	7768	15.6
	On	86.9	50.3	8675	7443	16.8
	Difference	-8.0%	4.1%	0.8%	-4.2%	7.2%
	Loc. Est. p-value	0.085*	0.014*	0.017*	0.107	0.031*
	Fixed Time p-value	0.077*	0.086*	0.031*	0.152	0.808
50%	Off	87.7	49.9	8659	7390	16.4
	On	84.1	51.0	8682	7252	17.2
	Difference	-4.2%	2.1%	0.3%	-1.9%	4.8%
	Loc. Est. p-value	0.262	0.032*	0.107	0.275	0.012*
	Fixed Time p-value	0.024*	0.027*	0.021*	0.031*	0.892
75%	Off	84.6	50.8	8682	7261	17.8
	On	84.3	50.9	8682	7303	18.0
	Difference	-0.4%	0.3%	0.0%	0.6%	1.3%
	Loc. Est. p-value	0.909	0.646	0.965	0.441	0.540
	Fixed Time p-value	0.029*	0.032*	0.019*	0.050*	0.494
100%	Off	80.0	52.0	8695	7246	20.7
	On	80.8	51.8	8689	7285	20.5
	Difference	1.0%	-0.4%	-0.1%	0.5%	-1.1%
	Loc. Est. p-value	0.620	0.314	0.214	0.155	0.599
	Fixed Time p-value	0.006*	0.006*	0.015*	0.043*	0.013*

CV = connected vehicle; Loc. Est. = location estimation.
In all cases, $n = 10$ and asterisks indicate $p < 0.10$.

It is worth noting that the GAP algorithm did not reduce benefits at high penetration rates, even when producing many incorrect vehicle location estimates. This suggests that the algorithm can remain active even during periods of high connected vehicle penetration rates without degrading the performance of the GAP algorithm.

CONCLUSIONS

- *It is possible to estimate the locations of some unequipped vehicles on an arterial or freeway with a reasonable degree of accuracy and to use these estimations to improve the performance of a connected vehicle mobility application.*

- *With adequate data on connected vehicle trajectories, the positions of a portion of unequipped vehicles on arterials and freeways can be estimated based on EV positions and behaviors.* On arterial through movements, more estimates are correct than incorrect using a distance error of approximately 7 meters (23 feet), and accuracy is substantially higher within 150 meters of an intersection. In tests based on empirical freeway vehicle trajectories, more estimates were correct than incorrect using a distance error of approximately 4 meters (13 feet) at penetration rates less than 30% and 5 meters (16 feet) at penetration rates less than 60%.

- *The arterial location estimation algorithm significantly improves queued vehicle count estimates simply by inserting vehicle estimates into observed gaps in the queue.* Queued vehicle count is an important metric for traffic signal timing applications.

- *The arterial location estimation algorithm can improve the queue length estimations at low EV penetration rates but only if there is one or more upstream intersections to generate inserted vehicles.* The research suggests the improvement decreases when there are too many upstream intersections (in the network analyzed, queue length estimation accuracy decreased from two to three upstream intersections). This indicates that the algorithm may overestimate the number of unequipped vehicles in a large network, an assumption that requires further investigation.

- *Provided the default probabilities are realistic, there is no significant performance difference between when inserted vehicles are assigned turning probabilities based on field-measured turning movement counts and when they are assigned turning probabilities based on default turning movement counts.*

- *The location estimation algorithms generate small improvements in the performance of certain connected vehicle mobility applications at low EV penetration rates.* On arterials, the traffic signal control algorithm PMSA was tested and significant improvements in delay, stopped delay, and speed occurred at penetration rates between 10% and 25%. Benefits were small and were statistically significant ($P < 0.05$) only in a few circumstances. No performance differences were found between assigning turning probabilities to inserted vehicles based on field-measured turning movements or assigning turning probabilities based on default turning movements. On freeways, a connected vehicle ramp metering algorithm called the GAP algorithm was tested. By using the freeway location estimation algorithm, the performance of the GAP algorithm was improved significantly at low EV penetration rates. Most benefits came between 10% and 50% connected vehicle penetration rates. At higher penetration rates, the freeway location estimation algorithm did not improve or degrade the performance of the GAP algorithm. The statistical significance of the improvement of the GAP algorithm was difficult to measure, as ramp metering often produces only minor improvements in simulation.

- *The arterial location estimation algorithm may worsen performance of a connected vehicle mobility application for arterials at high EV penetration rates.* When the arterial location estimation algorithm was tested on the PMSA, the system experienced higher delay, lower speeds, and increases in stops at 50% and 100% penetration. Without the arterial location estimation algorithm, the PMSA alone outperformed a coordinated-actuated timing plan at EV penetration rates of 25% to 100%. In general, the arterial location estimation algorithm should not be used at higher penetration rates.

- *With the freeway location estimation algorithm, vehicle estimates with lifespans of less than 1 second (i.e., vehicles that are able to move forward in the simulation at least one time step without being overlapped by an EV and therefore deleted) have lower initial position errors.* Based on this finding, the freeway location estimation algorithm does not consider vehicle insertions until they have survived at least 1 second.

- *Because the freeway location estimation algorithm bases its estimations off of vehicle interactions, some level of congestion is needed within or upstream of the study area to generate vehicle decelerations and provide adequate estimates.*

RECOMMENDATIONS

1. *The Virginia Center for Transportation Innovation and Research (VCTIR) in cooperation with VDOT's Operations Division should continue to assess the quality of vehicle data generated in a connected vehicle deployment to determine whether real-world data are of sufficient quality to be used in the two location estimation algorithms developed in this study.* Data can be collected from the connected vehicle test beds in Fairfax County, Virginia, and Blacksburg, Virginia, or from other deployments. Other developments and research in GPS accuracy, lane-level vehicle positioning, and acceleration sensor accuracy should also be tracked.

2. *If data quality is deemed accurate (from Recommendation 1) and if a connected vehicle application is evaluated in a field deployment, VCTIR should evaluate the use of the location estimation algorithms to attempt to improve the connected vehicle application's performance at low penetration rates.*

BENEFITS AND IMPLEMENTATION PROSPECTS

Benefits

The benefits to VDOT from implementing the recommendations provided are potential improvements in mobility on freeways and arterials, such as reduced delay and increased flow. These mobility benefits would be the direct result of an improved performance of connected vehicle mobility applications, such as ramp metering and traffic signal control, when few vehicles on the road are able to participate in a connected vehicle environment. Researchers from academia, government, and industry can also benefit from this study by using the location estimation algorithms to improve the performances of their own connected vehicle mobility applications at low connected vehicle penetration rates.

Feasibility of Implementing Each Recommendation

Recommendation 1 may be implemented by VCTIR as part of its general connected vehicle research.

Implementation of Recommendation 2 is contingent on an affirmative finding from Recommendation 1. Should this happen, VCTIR may track the progress of connected vehicle applications on the I-66 test bed in Fairfax County or in other deployments in Virginia and partner with the application's owner to integrate the location estimation algorithms.

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