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Integrating Position Uncertainty in Connected and Automated Vehicle Applications

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Integrating Position Uncertainty in Connected and Automated Vehicle Applications

A Dissertation submitted in partial satisfaction
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by

Nigel Williams

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The author of this dissertation is the primary author of these publications and the co-authors Prof. Matthew Barth and Dr. Guoyuan Wu directed and supervised the research which forms the basis for this dissertation.

ABSTRACT OF THE DISSERTATION

Integrating Position Uncertainty in Connected and Automated Vehicle Applications

by

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Doctor of Philosophy, Graduate Program in Mechanical Engineering
University of California, Riverside, December 2019
Dr. Matthew J. Barth, Chairperson

Connected and Automated Vehicles (CAVs) have the potential to greatly improve roadway safety, mobility, and associated environmental factors. To date, a large number of CAV applications have been developed and tested, both in the real world and in simulation. In nearly all cases, it is assumed that vehicle localization is sufficiently accurate at all times. Only a few studies have accounted for uncertainty in vehicle localization, which can be significant given CAVs' strong reliance on Global Navigation Satellite Systems (GNSS)-based systems for positioning. Positioning accuracy can vary both in time and space and is sometimes quite poor (>10 meters) in urban and other challenging environments for GNSS. This is a problem given that many CAV applications (e.g., Cooperative Adaptive Cruise Control) require at least lane-level, or submeter, accuracy.

This dissertation focuses on the gap between current (affordable) Connected Vehicle positioning technology and CAV applications' positioning requirements. As a first step, the positioning requirements of a wide range of CAV applications were qualitatively determined. The positioning attributes examined were: required accuracy, type (i.e., relative vs. absolute positioning), and update rate; and the "maximum benefit" accuracy. It was found that lane-level positioning accuracy is critical to enabling functionality in a large number of applications.

Next, the effect of position uncertainty on application performance was tested in a simulation environment. Two applications—an environmentally-friendly application for signalized intersections, and a safety-focused highway application—were examined. In both cases, it was found that application performance can degrade significantly (or outright fail) when the positioning accuracy is less than required.

Given the negative effect of position uncertainty on application performance, a position error-tolerant (PE-T) application was developed. A CAV application, (cooperative merging) was developed and modified so that it could function when position errors typical of an urban environment were present. In addition, it was found that adjusting the application in response to position error (by increasing inter-vehicle spacing) could increase application benefits in some scenarios. Another way in which this application is novel compared to most other existing cooperative merging strategies is that it can accommodate application penetration rates varying from 0% to 100%. In fact, significant safety, mobility, and environmental benefits are shown even at 20% penetration rate.

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1 Introduction

Transportation is a vital part of any sizable nation's economy, yet it often comes with negative impacts. Globally, 1.35 million people died in road traffic in 2016, making it the leading cause of death for people aged 5-29 around the world, and for people aged 1-54 in the United States [World Health Organization, 2018]. In addition, the average commuter in the United States wastes 54 hours per year in traffic, which is equivalent to a congestion cost of $166 billion across the entire country in 2017 [Schrank *et al*., 2019]. In the U.S., the transportation sector accounts for the largest portion of greenhouse gas emissions (see Figure 1.1) [U.S. EPA, 2019]. It is clear that road transportation has much room for improvement in the areas of safety, mobility, and the environment.

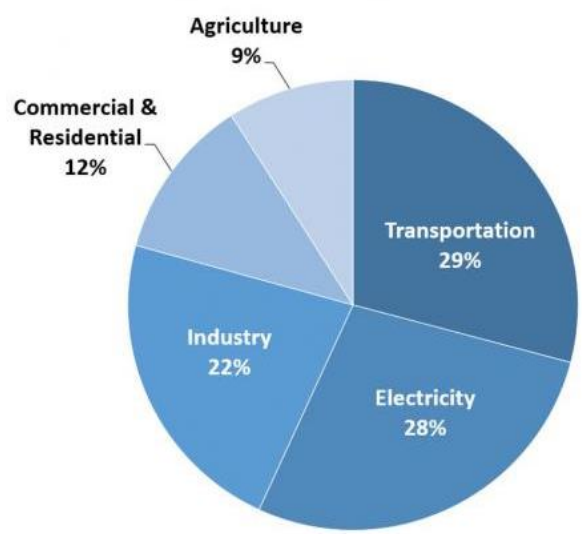

Figure 1.1: Total U.S. Greenhouse Gas Emissions by Economic Sector in 2017 [U.S. EPA, 2019]

Intelligent Transportation Systems (ITS) are one way to tackle some of these negative impacts associated with transportation. ITS strategies range from monitoring the roadways for better traffic control, to an automated highway system (AHS). An AHS has several control layers:

- Network – oversees highway network and performs routing according to traffic and desired directions
- Link – sets the desired speeds and platoon sizes according to link traffic flows
- Coordination – schedules interactive maneuvers of vehicles, such as merging and splitting
- Regulation – controls vehicle dynamics

Although a completely automated highway system is not in the near future, some aspects of the AHS can already be implemented as vehicle automation and connectivity continue to increase. As vehicles become increasingly connected, it becomes possible to improve the safety, mobility, and environmental impact of traffic through Connected Vehicle (CV) technology. CV technology utilizes V2V (vehicle-to-vehicle), V2I (vehicle-to-infrastructure), and V2X (vehicle-to-everything, such as pedestrians) communication to enable a wide range of applications, such as cooperative merging at freeway on-ramps. Various means may be used for this communication, with the most prominent being cellular (such as C-V2X, see [Vukadinovic *et al*., 2018]) and Dedicated Short Range Communications (DSRC [Harding *et al*., 2014]).

A number of Connected Vehicle (CV) applications have already been defined and developed around the world. Some applications are rigorously defined, others are already being implemented, while others are still being developed. The potential benefits of these applications are huge. A study showed that intersection-focused safety applications could minimize up to 575,000 crashes and 5,100 fatalities per year in the U.S. [Chang *et al.*, 2015]. The same study showed that a combination of V2I applications could reduce overall traffic delay by up to 27%, and carbon dioxide emissions and fuel consumption by up to 11% [Chang *et al.*, 2015].

1.1 Problem Statement

Many Connected Vehicle applications require vehicle position(s) as input. As the qualitative analysis in Chapter 3 shows, CV applications have widely varying positioning requirements in terms of the required accuracy, type, and update rate of positioning. The required accuracy ranges from knowing where the vehicle is in its lane, to simply knowing which section of roadway the vehicle is traveling on. As for the type of positioning, some applications require absolute positioning, whereas relative positioning is sufficient for others. For example, Cooperative Adaptive Cruise Control (CACC) requires the relative position and velocity of the vehicles, but the geographic location of the vehicles (e.g., which on-ramp the vehicles are closest to) may not matter. For other applications, such as routing, the absolute position of the vehicle on the map must be known to a certain degree of accuracy.

Different applications also require position update rates (of sufficient accuracy). Applications such as collision warning require the most frequent updates (on the order of 10 to 100 Hz), whereas an application like Eco-Speed Harmonization, which uses vehicle data to calculate the average speed on a roadway section, may only need position updates every 10 seconds or so.

Studies of CV applications generally assume positioning of the required accuracy and update rate to be continuously available (e.g., [Xia *et al.*, 2011; Shladover *et al.*, 2012]), which is not the case in the real world. The primary positioning method used by CVs is some type of GNSS (Global Navigation Satellite Systems) such as GPS. These systems can also utilize differential corrections and be aided by some dead reckoning [Hailemariam *et al.*, 2018]. In areas with a clear view of the sky, differential GNSS is often able to provide positioning with lane-level accuracy (i.e., accuracy sufficient to determine which lane the vehicle is traveling in, for which accuracy of <1 m is sufficient [Shladover and Tam, 2006]). However, when the GNSS receiver's sky view is obstructed (e.g., due to buildings, terrain, or trees), position errors on the order of ten meters can be quite common due to Non-Line of Sight (NLOS) error. For example, Figure 1.2 shows the error in the cross-street direction of three different GNSS receivers in a typical "urban canyon," where tall buildings line the streets. The receivers are similar to those used by CVs currently.

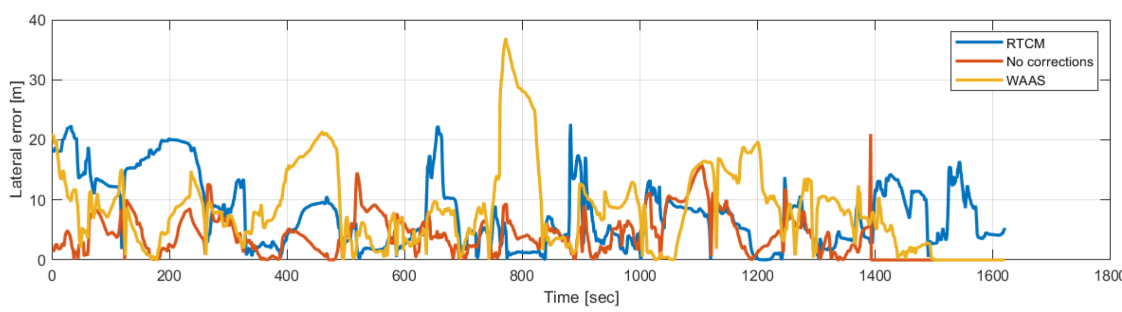

Figure 1.2: Example position error data in an urban canyon

The accuracy of GNSS positioning may be improved using other sources of positioning information (e.g., inertial sensors, ranging sensors, and map-matching). However, a low-cost positioning system that is capable of lane-level accuracy in most driving conditions has yet to be realized, as described in Chapter 2. Until such a system is available, there will be a gap between CV positioning and the positioning requirements of many CV applications. While it is often possible for CV applications to be used even if the positioning accuracy is less than required, the two case studies in Chapter 4 show that this can significantly reduce application benefits.

One way to address the current gap between positioning technology and CV application requirements, without increasing the cost of the positioning system, is to modify CV applications so that they can tolerate realistic levels of vehicle localization errors. For example, a simple way to do this is by de-activating an application when the position accuracy drops below the required level. A better approach would be to keep the application active but make it adaptable to the varying levels of accuracy. For example, an application for cooperative merging at highway on-ramps could increase the inter-vehicle spacing in response to higher position errors, and similarly decrease the vehicle spacing when the vehicle positioning accuracy is high, as is described in Chapter 5.

Other than directly increasing application benefits (by reducing the negative impact of position error on application performance), it is expected that making CV applications position error-tolerant (PE-T) would also accelerate the deployment of CV technology (bringing more of its benefits to society sooner) via the mechanism shown in

Figure 1.3. Increasing the application benefits would incentivize the deployment of CV technology, which would lead to more benefits due to the higher penetration of the technology. An increased deployment of CV technology would also increase the amount of data (e.g., probe vehicle data) available, which could be used to improve CV application performance. Also, the higher number of Connected agents (vehicles, infrastructure, or pedestrians) would allow for better collaborative positioning (see Section 2.1).

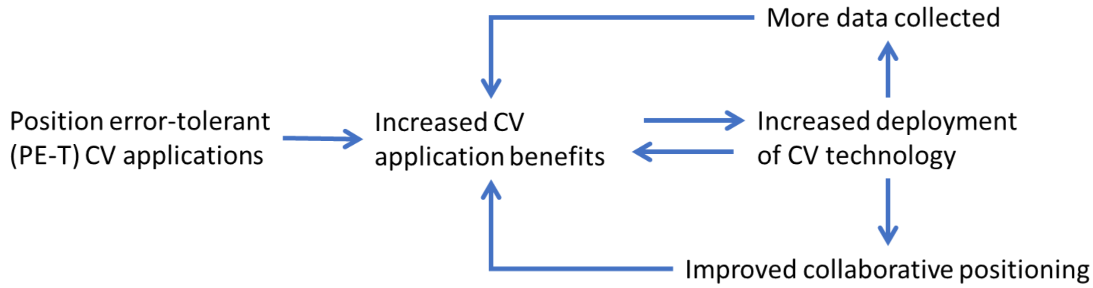

Figure 1.3: How PE-T applications could catalyze CV deployment

Another motivation for developing PE-T applications is that CVs will likely have varying levels of positioning technology, so it is preferable to have applications that can accept those different levels. The difference in positioning technology will likely become more pronounced as CVs become more widespread, with newer, high-end systems outperforming the older, low-end systems.

It is apparent that PE-T applications could play a significant role in accelerating the deployment of CV technology, allowing society to experience its benefits sooner. As a proof-of-concept of PE-T applications, Chapter 5 describes how a CV application was developed and modified to be tolerant of variable positioning error, then tested in simulation. This cooperative merging application can certainly improve safety at highway merging points, and under certain conditions, it also can improve traffic mobility and reduce the environmental impacts of traffic in the area.

In Chapter 0, another CV application for highways was developed, called Anticipatory Lane Change Warning (ALC). It prevents lane changes that are predicted to result in unsafe post-lane change situations. This application was also tested in simulation, and it was shown that it could reduce the number of potential crashes by up to 30%. The effect of position error on ALC is also discussed.

1.2 Contributions

Within this dissertation are contained several key contributions in the areas of Connected and Automated Vehicles (CAVs), cooperative merging, automated lane changing, and GNSS error modeling:

- A novel cooperative merging application has been developed, which is capable of handling GNSS position errors typical of an urban canyon. Unlike many other cooperative merging strategies in the literature, this application is also able to accept application penetration rates varying from 0 to 100%. In order to test this application, a GNSS position error model was created based on real-world data. Traffic simulation tests suggested that the application would improve safety, mobility, and environmental impact at highway merging areas.

This application can also be tuned (e.g., by increasing the spacing between vehicles) to reduce the negative impact of position error on application benefits.

- A real-time GNSS position error model was developed. This model has been used to generate realistic position errors (representative of certain GNSS receivers in an urban environment) as an input to CAV applications in traffic simulation tests. This is useful for CAV applications that require continuous GNSS positioning.
- An Anticipatory Lane Change algorithm was developed as a new CV application. It is an application for improving lane change safety, which was tested on highways but may also be applicable to surface streets. Simulation tests suggest that it could reduce the number of near-crashes by up to 30%, without changing the average speed of vehicles by more than 1%.

1.3 Organization

This dissertation is organized as follows. Background concepts and work related to the dissertation topic are presented in Chapter 2. Chapter 3 describes a qualitative analysis of the positioning requirements of a wide range of CV applications. Chapter 4 delves deeper into the topic with quantitative tests of the effect of insufficient positioning accuracy on two CV applications, Eco-Approach and Departure at Signalized Intersections and High Speed Differential Warning. Chapter 5 describes the development and evaluation of a position error-tolerant (PE-T) application for cooperative merging at highways. The algorithm and simulation tests of the developed ALC application are described in Chapter 6. In the final chapter, concluding remarks are given and future work pertaining to each of the chapters is suggested.

2 Related Work and Background

This chapter provides background on CAV applications, positioning for CAVs, and the simulation tools used to carry out much of the research in this dissertation. Section 2.1 describes the various positioning technologies that are feasible for use by CVs. Section 2.2 provides background on CV applications, focusing on the ones studied in Chapters 4-6. Section 2.3 describes the tools used to carry out traffic simulation, since these played an essential role in the studies described in this dissertation. Finally, Section 2.4 provides background on the Level of Service concept.

2.1 Positioning for Connected Vehicles

A positioning system can be evaluated in terms of the four Required Navigation Parameters (RNP): accuracy, integrity, continuity, and availability [Quddus, 2006]. *Accuracy* is defined as how far the measured position is from truth. *Integrity* is the measure of the trust that can be placed in the correctness of the information supplied by a navigation system. *Continuity* is a measure of how continuous (unbroken) the navigation solutions are, and *availability* is the percentage of time that the services of the system are usable by the navigator (satisfies the first three criteria).

This section describes positioning technologies available to Connected Vehicles. We classify these technologies (and, in Chapter 3, CV application requirements) based on accuracy, type of positioning (relative or absolute), and positioning update rate. We separate accuracy into four levels, which are described below:

1. None: No positioning required.

2. Coarse ("Where-on-road"): Accuracy sufficient to determine which roadway segment the vehicle is traveling on, and approximate location on it. Positioning accuracy is typically 5-10 meters. If the position error exceeds 10 meters, that location may be discarded (i.e., the accuracy drops to "None").
3. Lane-level: Which lane the vehicle is in (the "absolute positioning" case, explained below) or the number of lanes between vehicles ("relative positioning" case, explained below). Given that a typical passenger car is 1.8 m wide, the position error must be less than 0.9 m. This way, the measured position will fall within the correct lane, even if one side of the vehicle is on the lane edge. Submeter accuracy is also declared necessary for correct lane assignment in [Shladover and Tam, 2006].
4. Where-in-lane: Where-in-lane accuracy is important for automated driving functions such as stopping at a stop bar and lane keeping. While 0.9 m accuracy may be sufficient for lane placement, it is not sufficient for these tasks. Therefore, we define 0.1 m as the required accuracy. This is also the required accuracy for collision avoidance applications in [FRP, 2017].

Another important positioning requirement is positioning type (relative or absolute). Non-GNSS sensors such as radar can measure the position of one vehicle relative to another (relative positioning) but does not give the vehicle's location (absolute position) without some kind of feature map (in this case, a map of radar-detectable features such as described in [Ward and Folkesson, 2016]).

Different applications require sufficiently accurate position updates at different rates. Applications such as collision warning require the most frequent updates (on the order of 10 to 100 Hz), whereas an application like Eco-Speed Harmonization, which uses vehicle data to calculate the average speed on a roadway section, may only need the position data to be updated every 10 seconds or so. Thus, another positioning requirement we identify is the maximum allowable time between position updates. We separate this value into three levels: tenths of seconds, seconds, and tens of seconds.

2.1.1 Global Navigation Satellite Systems

Global Navigation Satellite Systems (GNSS) are generally used as the primary source of position information for CVs. This is because a GNSS receiver can determine a user's three-dimensional position anywhere on Earth with line-of-sight to four or more GNSS satellites. The basic operating principle of GNSS is estimation of the distance from each satellite to the receiver, referred to as a pseudorange [Farrell *et al*., 2016]. Consumer-grade GNSS receiver accuracy is usually about 10 meters [Farrell *et al*., 2016]. This level of accuracy is generally sufficient to determine which road segment a vehicle is on, but not which lane it is in. The first GNSS was the Global Positioning System (GPS) launched by the United States in 1973; since then, multiple other GNSS constellations have come online, such as the European Union's Galileo, Russia's GLONASS, and China's Beidou [Wang *et al*., 2019]. Using multiple constellations improves the availability and accuracy of GNSS positioning due to the increased number of visible satellites [Walsh *et al*., 1997; Wang *et al*., 2012; Liu and Li, 2017].

Differential corrections may be used to improve the accuracy of GNSS so that it can provide consistent lane-level accuracy [see, e.g., Du and Barth, 2008]. This technique is referred to as Differential GNSS (DGNSS). DGNSS may be differential pseudorange or differential phase, though it usually refers to differential pseudorange. Differential pseudorange enables accuracy of 1 to 3 m, while differential phase improves it further to a few centimeters (where-in-lane accuracy) [Farrell, 2008; Uradzinski *et al.*, 2008]. The basic mechanism by which accuracy is improved, for both differential pseudorange and differential phase, is explained below.

Differential pseudorange utilizes the fact that GNSS receivers operating in close proximity experience similar "common mode" errors, such as ionospheric and tropospheric delay. These errors are shown in the pseudorange equation:

$$P_r^s = \rho_r^s + c(dt_r - dT^s) + I_r^s + T_r^s + \varepsilon_r^s \tag{2.1}$$

where P_r^s is the measured pseudorange, ρ_r^s is the actual pseudorange, $c(dt_r - dT^s)$ is the term containing clock error, I_r^s and T_r^s are errors due to ionospheric and tropospheric delay, respectively, and ε_r^s is error due to receiver noise and multipath.

A base station with known coordinates can determine these time-varying errors and broadcast corrections to nearby Differential GNSS receivers. Differential phase builds on the accuracy improvement of differential pseudorange. Once the common mode errors are eliminated, it is possible to use the carrier phase information of the GNSS signal, yielding accuracy approximately 100 times better than differential pseudorange [Farrell, 2008]. This technique is commonly known as Real Time Kinematic (RTK). In the past, RTK was typically in the domain of expensive dual-frequency receivers. Single-frequency receivers are less expensive, but require more time to obtain an RTK fixed-integers solution. This time can be shortened by using multiple GNSS constellations instead of just one [Odijk *et al.*, 2012].

The drawback of DGNSS is that it requires a separate "correction" signal, using a known set of local base stations. These corrections can be received by various means, including information on the Internet (e.g., NTRIP (Networked Transport of RTCM via Internet Protocol) [Weber *et al.*, 2005]), satellite signal (e.g., WAAS [Pullen *et al.*, 2002]), or a separate DSRC broadcast. Comparable accuracy to differential pseudorange GNSS may be achieved without the need for a base station by directly sharing pseudorange signals among vehicles [Alam *et al.*, 2013; de Ponte Müller *et al.*, 2014; Lassoued *et al.*, 2017]. This is known as collaborative positioning. However, since there is no reference point with known coordinates, the improved accuracy applies only to relative positioning.

2.1.1.1 NLOS Error

A major weakness of GNSS positioning is that large (on the order of 10 m) position errors can be common in urban and other areas where the sky view is partially blocked. This is the case even if using differential corrections. The mechanism by which such error is produced is known as the Non-Line of Sight (NLOS) phenomenon [Groves *et al.*, 2012]. When the receiver's view of the sky is blocked, the following may occur, which can worsen GNSS positioning accuracy or even availability: 1) fewer satellites may be visible, and 2) satellite signals may reach the receiver via a reflected path (for example, reflected off a building in an urban environment—see Figure 2.1). There are two problems associated with (1). First, if less than 4 satellites are visible, it is impossible to compute a 3D position solution using GNSS alone. Second, even if the positioning solution is still available, a smaller visible portion of the sky means a smaller area over which visible satellites can be scattered. This leads to poorer satellite geometry and hence lower positional accuracy.

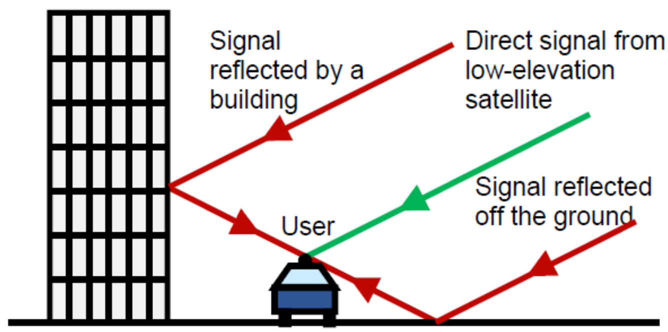

Figure 2.1: Example of NLOS error [Groves *et al*., 2012]

The ramifications of (2) are that the receiver may receive a satellite's signal via the reflected ("NLOS") path, which erroneously increases the receiver's estimate of that satellite's pseudorange. The satellite's signal may even reach the receiver via two or more paths (multipath), which also introduces position error. NLOS errors on the order of ten meters are easily possible [Maier and Kleiner, 2010; Gu *et al*., 2015]. While NLOS error is generally worst in built-up urban environments, it can also be caused by terrain or foliage (e.g., leaves may weaken the GNSS signal). The amount of error varies based on factors such as: the height/geometry of the obstructions, the time of day (affecting satellite geometry), and antenna height.

2.1.1.2 Dealing with NLOS Error

There are various ways to deal with NLOS error. Bressler et al. classified methods of dealing with NLOS error into four general approaches: ignore, mitigate, identify, and exploit [Bressler *et al*., 2016]. "Ignore" is self-explanatory, and the consequences of using this approach are illustrated in Chapter 4. Mitigation techniques (e.g., different antenna design) attempt to reduce the magnitude of NLOS error. Identifying a NLOS signal allows it to be eliminated from the position solution or exploited. An example of exploitation is using 3D building models and ray-tracing to calculate the extra distance traveled by a NLOS signal, effectively allowing it to be used to calculate a pseudorange. "Avoid" simply refers to avoiding areas with more NLOS error. This could be accomplished using a routing application, given that there are data on which areas tend to have more severe NLOS error.

Various methods for reducing the negative impact of NLOS error have been researched [Breßler *et al*., 2016]. One type of method uses three-dimensional (3D) building information together with satellite ephemeris (orbit) data. For example, a 3D map may be used to calculate the number of satellites that should be visible at a particular time and place. This technique has been used to improve GNSS-based services such as navigation [Suh and Shibasaki, 2007; Asavasuthirakul and Karimi, 2013], by routing road users through areas with better satellite visibility. 3D building models may also be used to calculate which GNSS signals should be LOS, and which ones should not, at a particular time and location. When using this technique to reduce the GNSS position error, it is referred to as 3DMA (3D map-aided) GNSS [Gu *et al*., 2015; Groves *et al*., 2012; Miura *et al*., 2015].

2.1.2 Other Positioning Technologies

Techniques to enhance the absolute positioning accuracy of GNSS include: integration with sensors that measure vehicle motion ("ego motion sensors"), and map-matching of the vehicle position. Ego motion sensors typically part of Inertial Navigation Systems (see, e.g., [Farrell, 2000; Redmill *et al*., 2001]) and Encoder Navigation Systems (these might use wheel speed sensors and steering angle encoders [Rezaei and Sengupta, 2007], wheel turn sensors [Hohman *et al*., 2000], etc.). While these sensors can be used in conjunction with GNSS to provide long-term stable accuracy, inertial navigation systems (e.g., dead reckoning) by themselves accumulate error over time and therefore are not dependable during long periods of time without accurate position updates from other sources such as GNSS.

Another technique used to improve positional accuracy is map-matching with sufficiently accurate maps. Map-matching (see, e.g., [Greenfeld, 2002]) constrains the vehicle position to the roadway, eliminating or partially correcting erroneous position estimates that appear to fall outside the roadway. However, this technique requires a map database, and cannot guarantee lane-level accuracy. Ranging sensors can be used for positioning independently of GNSS. Vehicle-based ranging sensors detect other vehicles and measure their position and speed relative to the sensor-equipped vehicle. Such sensors include camera, radar, and LiDAR (Light Detection And Ranging); in order of increasing cost and accuracy. These sensors are typically capable of lane-level or higher accuracy within a range of about 50 m [Sakr and Bansal, 2016]. However, such sensors add to the vehicle cost.

Ranging sensors may also be used for *absolute* positioning when combined with a feature-based map. LiDAR is probably the most prominent example [Farrell *et al*., 2016], although radar and vision may be used too. A vehicle equipped with multiple radar sensors may traverse a route, building a map of radar-detected features that can later be used for localization [Ward and Folkesson, 2016]. Computer vision may be used for absolute positioning by, for instance, determining distance and orientation to a landmark with known coordinates [Kogan *et al*., 2016].

2.2 CAV Applications

Many Connected Vehicle applications have already been defined and developed around the world. A list of CV applications is maintained at the USDOT's Connected Vehicle Reference Implementation Architecture (CVRIA) website [USDOT, 2017]. The list contains 88 applications as of November 2019. Each application is accompanied by a text description, system architecture diagram, and further information. Some applications are rigorously defined, others are already being implemented, and still others are in the process of being further developed. Several of these applications are being tested in pilot deployments of CV technology across the U.S., such as the Connected Vehicle Pilot Deployment [USDOT ("Connected Vehicle Pilot Deployment Program")].

Connected Vehicle applications can be grouped into three main types, based on the application objective: safety, mobility, and environmental applications. Safety applications are intended to reduce the number and/or severity of accidents, mobility applications are mainly designed to reduce travel time and increase roadway capacity, and environmental applications are designed to reduce energy consumption and/or pollutant emissions. A list of these applications can be found in Tables 3.1-3.3.

2.2.1 Eco Approach and Departure

Eco-Approach and Departure at Signalized Intersections (EAD) provides speed guidance to a vehicle so that it can pass through a signalized intersection in an environmentally-friendly manner [Altan *et al.*, 2017]. This requires that both the vehicle and the traffic signal be equipped with wireless communication technology such as Dedicated Short Range Communications (DSRC) radios.

The basic idea is that once the vehicle enters the communication range of a signalized intersection (nominally 300 m for DSRC), it obtains the lane-level Signal Phase and Timing (SPaT) information of the intersection, such as current phase (i.e., green, yellow, or red) and time until phase change [SAE Intl., "Dedicated Short Range Communications (DSRC) Message Set Dictionary"]. Using this information, the vehicle can plan its speed trajectory in order to reduce energy use. For example, if the vehicle cannot make it through the intersection on the current green phase without exceeding the speed limit, the driver will be advised to start coasting to a stop rather than keep pressing on the gas pedal. This corresponds to "Scenario 3" (red line) in Figure 2.2. All of the scenarios are described below.

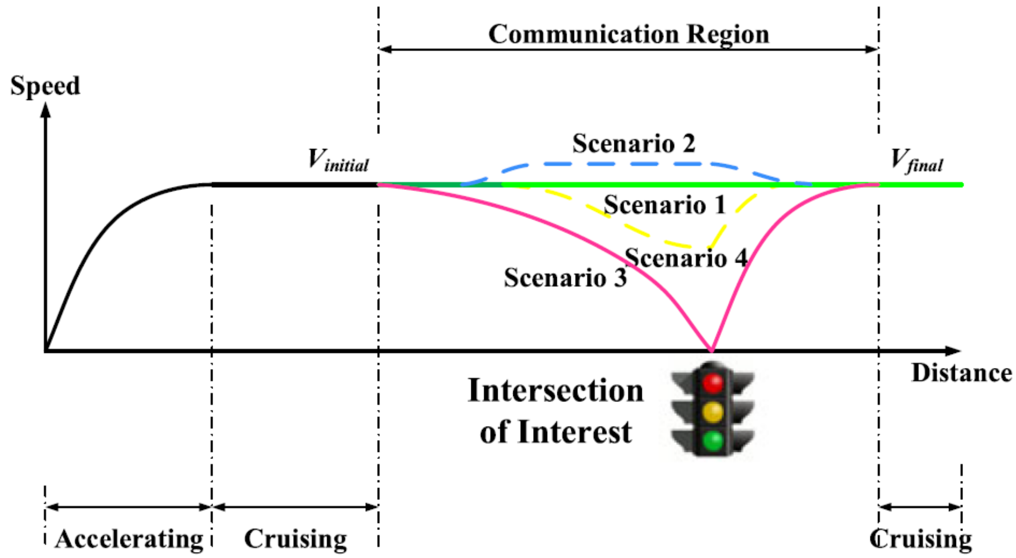

Figure 2.2: EAD scenarios [Altan *et al*., 2017]

EAD Scenarios:

- Scenario 1: No speed change necessary in order to pass through the intersection on green.
- Scenario 2: Vehicle must accelerate in order to pass through on green.
- Scenario 3: Vehicle will have to stop, so it is advised to begin coasting.
- Scenario 4: Vehicle decelerates pre-emptively in order to avoid coming to a complete stop.

Of course, vehicles in front may limit the EAD-equipped vehicle's speed. This is modeled in the simulation by the EAD-equipped vehicle reverting to the speed calculated by the default car-following model, if it is less than the speed recommended by EAD.

2.2.2 High Speed Differential Warning

The purpose of the High Speed Differential Warning application is to reduce the likelihood of a collision by identifying high speed differentials between the application-equipped vehicle and nearby vehicles, and providing a warning to the driver [Li *et al.*, 2017]. For example, if a vehicle ahead of a HSDW-equipped vehicle suddenly slows down (and both vehicles are equipped with wireless communication technology such as DSRC), the driver of the HSDW-equipped vehicle may be advised to decelerate. This corresponds to Scenario 1 in Figure 2.3. All 5 scenarios depicted in Figure 2.3 are listed below, together with their corresponding driver response.

HSDW Scenarios:

1. Slow vehicle in current lane. Driver decelerates to reduce the speed differential.
2. Fast vehicles upstream or slow vehicles downstream in the target lane. Driver does not change lanes or changes lanes more cautiously.
3. Slow vehicle changing to current lane. Driver decelerates to reduce the speed differential.
4. Slow vehicle merging to current lane. Driver decelerates to reduce the speed differential.
5. Fast vehicles upstream on the mainline. Driver waits for a safe occasion to merge.

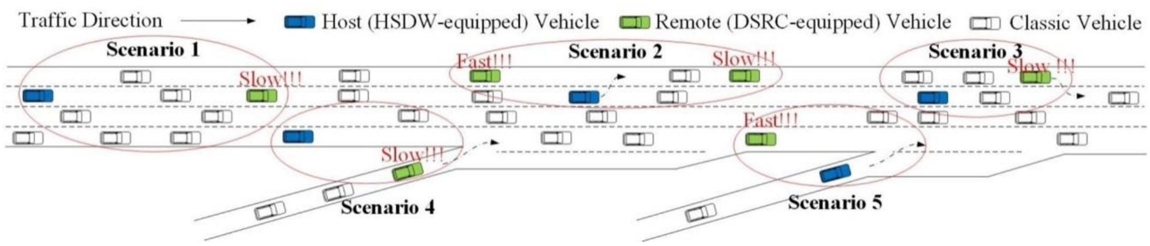

Figure 2.3: High Speed Differential Warning Scenarios [Li *et al*., 2017]

2.2.3 Cooperative Merging

Merging refers to when two (or more) streams of vehicles converge into one stream. This is a common occurrence at traffic facilities such as roundabouts, where vehicles from streets must merge into the roundabout traffic, and highways, where vehicles merge onto the highway from on-ramps. In these cases, we refer to the stream being merged into as the "mainline." CAV technology may be used to improve the merging process, for example through so-called "cooperative merging." This involves adjusting the speeds of merging and/or mainline vehicles to achieve benefits such as greater safety or comfort. A study conducted by Davis suggested that cooperative merging can prevent the transition from free-flow to synchronous flow, which is the intermediate stage before a traffic jam [Davis, 2006].

Merging strategies can be classified into centralized and decentralized approaches. In a centralized approach, at least one task is globally decided for all vehicles by a central controller; whereas in decentralized control, each vehicle determines its own control policy based on information received from other vehicles or some coordinator [Rios-Torres and Malikopolous, 2016].

Decentralized approaches include use of a “virtual” vehicle: for example, a vehicle on one lane may “follow” a vehicle on the other lane as if it were in its own lane [Lu *et al*., 2004]. Wang et al. developed a distributed consensus-based merging algorithm and tested it in simulation [Wang *et al*., 2018]. In the tested scenarios, it improved the mobility and environmental impact of the network.

Zhao et al. investigated an optimal merging strategy for vehicles at roundabouts, including mixed-traffic (varying percentages of vehicles using the strategy) scenarios [Zhao *et al*., 2018]. They found that a high penetration rate (>80%) of equipped vehicles was necessary to achieve substantial savings in travel time and energy use, though this could be partially due to the near-capacity demand of the network. Another study of automated merging in mixed traffic showed mobility benefits when the penetration rate was 50% or higher [Rios-Torres and Malikopoulos, 2018].

2.2.4 Automated Lane Changes

A number of researchers have developed algorithms for performing automated lane changes. Nilsson et al. developed a low-complexity lane change maneuver algorithm that determines if, when (the tactical aspect), and how (the control aspect) to perform a lane change [Nilsson *et al*., 2016]. Luo et al. developed a maneuver that includes both trajectory planning and tracking [Luo *et al*., 2016]. This method is notable in that it can abort the lane change midway, if necessary. Other approaches handle both lane changing and car following [Wang *et al*., 2015; Dang *et al*., 2015].

The role of wireless communication technologies in lane changing and collision prevention has received significant attention in the literature. Chakroun and Cherkaoui developed a lane change advisory application and studied its network-wide impact on mobility [Chakroun and Cherkaoui, 2016]. Researchers examined the use of V2V communication in reducing the number of secondary collisions caused by an accident, and found that a technology penetration of approximately 25% was sufficient to drastically reduce the number of accidents [Busson *et al.*, 2011]. The effect of warning communications on safety and capacity in a vehicle string was analyzed in [Mourllion *et al.*, 2006].

2.3 Simulation Tools

This section describes the traffic simulation tools that were used to carry out the work described in this dissertation. Traffic simulation modeling is an often-used tool to study "what-if" scenarios in transportation, such as future roadway design and the projected impact of CAV technology. Simulation resolution may range from microscopic to macroscopic. Microscopic simulation models the movements of individual vehicles, mesoscopic simulation deals with the average flows/speeds of links (segments of roadway), and macroscopic simulation can be used to perform nationwide predictions. In the context of CAV applications, microscopic simulation is most commonly used because it can model automated vehicle behavior in a CAV application(s).

Two traffic microsimulation packages were used in this dissertation: Quadstone Paramics [Quadstone Paramics, 2016] and PTV Vissim [PTV Group, 2018]. Both packages allow detailed simulation of the impact of CAV technology on vehicle trajectories, and the resulting ramifications for safety, mobility, and the environment in the study area (the "simulation network"). CAV technology and behaviors can be implemented in the traffic simulation models using an Application Programming Interface (API). The API allows users to access and modify simulation data (e.g., collecting second-by-second vehicle speed, modifying vehicle behavior). This functionality was also used to simulate position error, and to collect second-by-second speed and other data.

When using traffic simulation, multiple runs are generally conducted for each tested configuration. Due to the stochastic nature of traffic, simulation results may vary greatly depending on random variables such as vehicle input times. These random variables correspond to what is called the random seed in such simulation packages as Paramics and VISSIM. If a simulation is run twice using the same random seed number, the results will be exactly the same. However, changing the random seed will almost certainly make the results different. Therefore, for each configuration (combination of simulation parameters) to be tested, multiple runs were made, each with a different random seed.

Safety performance throughout the simulation network can be estimated using the Surrogate Safety Assessment Model (SSAM) developed by U.S. Federal Highway Administration (FHWA) [Gettman *et al*., 2008]. In SSAM, the safety performance is evaluated in terms of "conflicts". A "conflict" is when two or more road users approach each other such that there is a risk of collision if their movements remain unchanged. A high correlation has been demonstrated between conflicts and crashes [Gettman *et al*., 2008]. Mobility performance was measured in terms of travel times and speeds, all of which were obtainable through the software API. Environmental metrics such as energy use and emissions of carbon monoxide (CO), carbon dioxide (CO_2), hydrocarbons (HC), nitrous oxides (NO_x), and particulate matter ($PM_{2.5}$), were estimated using the U.S. Environmental Protection Agency's Motor Vehicle Emission Simulator (MOVES) model [U.S. EPA, 2011].

2.4 Level of Service

Level of Service is a measure of the quality of vehicle traffic service. It is given as a grade, with A being the best and F being the worst. The Highway Capacity Manual defines Levels of Service (LOS) for both highways and arterial roads [Highway Capacity Manual, 2010]. For highways, LOS is defined based on the vehicle density (see Figure 2.4). LOS A represent free-flow, where drivers are able to maneuver freely and with hardly any constraint imposed by other vehicles. LOS F represents traffic jam conditions, where vehicles move in lockstep.

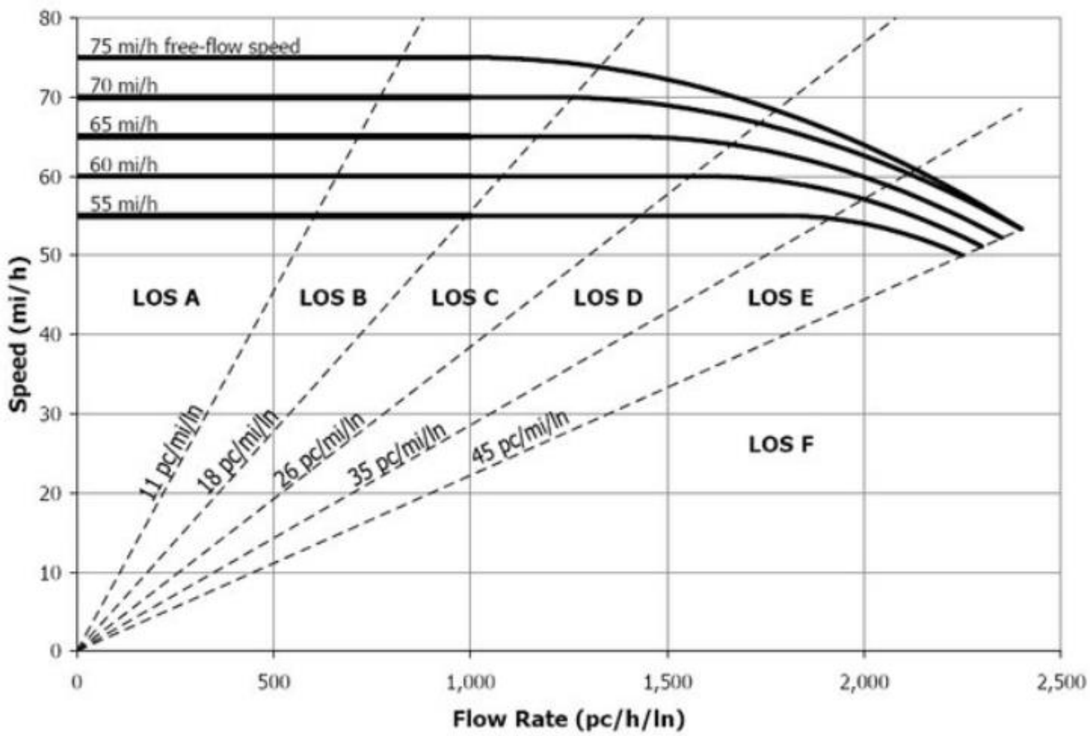

Figure 2.4: Definition of Level of Service for Freeway Segment [Highway Capacity Manual, 2010]

3 Analysis of the Positioning Requirements of CV Applications

3.1 Overview

Most studies of CV applications assume vehicle positions to be perfectly known. However, given the current state of vehicle positioning technology, that is not the case. To investigate whether there is a gap between what the positioning technology can provide, and the positioning requirements of CV applications, it is first necessary to know what those positioning requirements are. Therefore, the objective of this chapter is to qualitatively identify the positioning attributes of the CV applications listed in the CVRIA, namely the required accuracy, the "maximum benefit" accuracy, required positioning type (relative or absolute), and update rate. These attributes are explained in Section 3.2. The results for each application are grouped by application type (safety, mobility, environmental) in Section 3.3. This section also summarizes the trends in positioning attributes across groups of applications. The chapter ends with a summary and discussion.

3.2 Analysis Methodology

The vehicle positioning attributes of each CV application listed in the CVRIA were identified using the information accompanying the application. These positioning attributes are explained below:

- Required accuracy: The minimum level of accuracy required for basic functionality of the application. We use four levels: where-in-lane, lane-level, coarse, and none (see Section 2.1 for an explanation of these).
- The "maximum benefit" accuracy: Many applications gain significant benefits (additional knowledge or functionality) at a higher-than-required level of positioning accuracy [Farrell *et al*., 2016]. If so, the highest such level is considered the "maximum benefit" accuracy, and the benefit(s) are listed under that level. Sometimes these benefits, such as "automatic vehicle reaction" for the Control Loss Warning application, require some level of vehicle automation, which may not be featured on all Connected Vehicles.
- Required type of positioning: Whether absolute or relative positioning is needed. If both are required, "absolute" is indicated. This is because relative position can be derived from absolute positions, but not vice versa. Absolute positioning also requires map information of sufficient accuracy [Farrell *et al*., 2016]. Note that the positioning type may change at a higher accuracy level than required.
- Update interval: The maximum time that may elapse between position updates of the required accuracy, in order for the application to function properly. We classify this interval into three levels: tenths of seconds, seconds, and tens of seconds.

3.3 Analysis Results

The positioning requirements of the applications listed at CVRIA were analyzed as discussed in Section 3.2. Table 3.1 shows the results for Safety applications, Table 3.2 for Mobility applications, and Table 3.3 for Environmental applications. In the tables, a checkmark indicates the required positioning accuracy. The positioning type is absolute unless the word “relative” appears in parentheses. Text written under a higher level of accuracy indicates significant benefits (additional knowledge or functionality) gained at that level. The subsections following Tables 3.1-3.3 provide summary statistics about the positioning attributes.

Table 3.1: Safety Connected Vehicle Applications

		No Positioning	Coarse Positioning	Lane-Level Positioning	Where-in-Lane Positioning	Max. Time between Position Updates (s)
Transit Safety	Transit Pedestrian Indication		✓	Pedestrian-bus proximity warning (relative)	Pedestrian-bus collision warning (relative)	1
	Transit vehicle at Station/Stop Warnings		✓	Detection of transit vehicle pulling in or out		1
	Vehicle Turning Right in Front of a Transit Vehicle			✓ (relative)		0.1
V2I Safety	Curve Speed Warning		✓	Whether speed within curve is likely to exceed recommendation		1
	In-Vehicle Signage		✓	More accurate “virtual sign” location		1
	Oversize Vehicle Warning		✓	Accurate distance to low-clearance zone		1
	Pedestrian in Signalized Crosswalk Warning		✓	Detection of vehicle/pedestrian in crosswalk		0.1
	Railroad Crossing Violation Warning		✓ (relative)	Better collision prediction (relative)		1
	Red Light Violation Warning			✓		1
	Reduced Speed Zone Warning / Lane Closure		✓	Whether current lane will be closed ahead		1
	Restricted Lane Warnings		✓	Whether vehicle is in restricted lane		1
	Spot Weather Impact Warning		✓	Lane-specific weather impacts (e.g., ice)		1
	Stop Sign Gap Assist			✓		0.1
	Stop Sign Violation Warning			✓		1
	Warnings about Hazards in a Work Zone			✓		0.1
	Warnings about Upcoming Work Zone		✓	Whether current lane will be obstructed, etc.		1
V2V Safety	Blind Spot Warning + Lane Change Warning			✓ (relative)	More accurate warning (relative)	0.1
	Control Loss Warning		✓ (relative)	Distance/direction to out-of-control vehicle	Automatic vehicle reaction	0.1

		No Positioning	Coarse Positioning	Lane-Level Positioning	Where-in-Lane Positioning	Max. Time between Position Updates (s)
				(relative)		
	Do Not Pass Warning			✓ (relative)		0.1
	Emergency Electronic Brake Light		✓ (relative)	Lane of braking vehicle (relative)		0.1
	Emergency Vehicle Alert		✓ (relative)	Lane of emergency vehicle (relative)		1
	Forward Collision Warning			✓ (relative)	Fewer false positives/negatives (relative)	0.1
	Intersection Movement Assist			✓	Improved collision prediction (relative)	0.1
	Motorcycle Approaching Indication		✓ (relative)	Lane of motorcycle (relative)	Collision prediction (relative)	1
	Pre-crash Actions			✓ (relative)	Improved collision prediction (relative)	0.1
	Situational Awareness		✓ (relative)	Lane-specific warnings (relative)		1
	Slow Vehicle Warning		✓ (relative)	Lane of slow vehicle (relative)		1
	Stationary Vehicle Warning		✓ (relative)	Lane of stationary vehicle (relative)		0.1
	Tailgating Advisory			✓ (relative)	Fewer false positives/negatives (relative)	0.1
	Vehicle Emergency Response	✓	Approximate crash location	Lane of crash	Diagnosis of how accident happened	10

Table 3.2: Mobility Connected Vehicle Applications

		No Positioning	Coarse Positioning	Lane-Level Positioning	Where-in-Lane Positioning	Max. Time between Position Updates (s)
Border	Border Management Systems	✓				
Commercial Vehicle Fleet Operations	Container Security	✓				
	Container/Chassis Operating Data	✓	Container locations			
	Electronic Work Diaries		✓	Driving pattern and other detailed information		10
	Intelligent Access Program		✓	More detailed monitoring		10
	Intelligent Access Program – Mass Monitoring		✓	More detailed monitoring		10
Commercial Vehicle Roadside Operations	Intelligent Speed Compliance		✓	Speed may be derived from position		1
	Smart Roadside Initiative		✓	More accurate geofence		1
Electronic Payment	Electronic Toll Collection	✓		Required in the absence of an RF transponder		1
	Road Use Charging		✓			10
Freight Advanced Traveler Information Systems	Freight Drayage Optimization		✓			1
	Freight Specific Dynamic Travel Planning		✓			1
Planning and Performance Monitoring	Performance Monitoring and Planning		✓	Lane-level speed and travel time data		10
Public Safety	Advanced Automatic Crash Notification Relay		✓	Lane of crashed vehicle		1
	Emergency Communications and Evacuation		✓			10
	Incident Scene Pre-Arrival Staging Guidance for Emergency Responders		✓	Better information for staging of assets		1
	Incident Scene Work Zone Alerts for Drivers and Workers		✓	Lane information for guidance around incident		1

		No Positioning	Coarse Positioning	Lane-Level Positioning	Where-in-Lane Positioning	Max. Time between Position Updates (s)
Traffic Network	Cooperative Adaptive Cruise Control (CACC)			✓ (relative)	Smaller gaps possible for car-following, lane changes (relative) Lane keeping (absolute)	0.1
	Queue Warning		✓ (relative)	Lane of queue (relative)		1
	Speed Harmonization		✓	Can use lane-level vehicle trajectories to calculate recommended speed		1
	Vehicle Data for Traffic Operations		✓	Better incident detection		1
Traffic Signals	Emergency Vehicle Preemption		✓	Can plan route through traffic and direct other vehicles to make way (relative)		1
	Freight Signal Priority		✓	Whether vehicle is in left-turn bay (and hence requires left-turn green)		1
	Intelligent Traffic Signal System		✓	Number of vehicles arriving in each lane/direction of travel		1
	Pedestrian Mobility				✓	1
	Transit Signal Priority		✓	Whether vehicle is in left-turn bay (and hence requires left-turn green)		1
Transit	Dynamic Ridesharing		✓	High-occupancy lane usage data		10
	Dynamic Transit Operations		✓			10
	Integrated Multi-Modal Electronic Payment	✓		Required in the absence of RF transponder		1
	Intermittent Bus Lanes		✓	Whether vehicle is in bus lane		1

		No Positioning	Coarse Positioning	Lane-Level Positioning	Where-in-Lane Positioning	Max. Time between Position Updates (s)
	Road ID for the Visually Impaired		✓	Location of appropriate bus		1
	Smart Park and Ride System			✓		10
	Transit Connection Protection		✓			10
	Transit Stop Requested		✓			1
Traveler Information	Advanced Traveler Information Systems	✓	Allows use of probe vehicles for collection of traffic and other data	Lane-level data from probe vehicles		
	Traveler Information-Smart Parking		✓	Location of empty parking spaces		

* Also requires identification of vehicle as freight/transit vehicle

Table 3.3: Environmental Connected Vehicle Applications

		No Positioning	Coarse Positioning	Lane-Level Positioning	Where-in-Lane Positioning	Max. Time between Position Updates (s)
AERIS/ Sustainable Travel	Connected Eco-Driving	✓	Eco-driving advice based on road grade, local traffic speeds…	Interactions with nearby vehicles (relative)		10
	Dynamic Eco-Routing		✓			10
	Eco- Approach and Departure at Signalized Intersections		✓	Can stop behind queue at intersection	Automatically stop at stop bar	1
	Eco-Cooperative Adaptive Cruise Control			✓ (relative)	Smaller gaps possible for car-following, lane changes (relative) Lane keeping (absolute)	0.1
	Eco-Freight Signal Priority		✓	Whether vehicle is in left-turn lane (requires left-turn green)		1
	Eco-Integrated Corridor Management Decision Support System	✓	Link-level emissions data			10
	Eco-lanes Management		✓	Whether vehicle is in eco-lane		10
	Eco-Multimodal Real-Time Traveler Information	✓	Allows use of probe vehicles for collection of traffic and other data	Lane-level data from probe vehicles		10
	Eco-Ramp Metering			✓		1
	Eco-Smart Parking		✓	Parking space locations		1
	Eco-Speed Harmonization		✓	Lane-level recommended speeds		1
	Eco-Traffic Signal Timing		✓	Number of vehicles in each lane/direction of travel		1
	Eco-Transit Signal Priority		✓	Whether vehicle is in left-turn lane		1

		No Positioning	Coarse Positioning	Lane-Level Positioning	Where-in-Lane Positioning	Max. Time between Position Updates (s)
				(requires left-turn green)		
	Electric Charging Stations Management	✓		Wireless charging at parking space		
	Low Emissions Zone Management		✓	Whether vehicle is crossing zone boundary		1
	Roadside Lighting		✓			1
Road Weather	Enhanced Maintenance Decision Support System		✓			1
	Road Weather Information and Routing Support for Emergency Responders		✓			1
	Road Weather Information for Freight Carriers		✓			1
	Road Weather Information for Maintenance and Fleet Management Systems		✓			1
	Road Weather Motorist Alert and Warning		✓			1
	Variable Speed Limits for Weather-Responsive Traffic Management		✓			1

* Also requires identification of vehicle as freight/transit vehicle

3.3.1 All Applications

82% of all applications require either no or "coarse" positioning for basic functionality; the remainder require lane-level positioning. Of the applications which require positioning, about three-quarters require absolute positioning, and the rest need only relative positioning.

Figure 3.1 and Figure 3.2 break down these statistics by application type. Regarding the position accuracy (Figure 3.1), most of the applications requiring lane-level accuracy are in Safety; 90% of the Mobility and Environmental applications require either coarse positioning or none at all. Regarding the positioning type (Figure 3.2), Safety contains most of the relative positioning applications. When positioning is required by a Mobility or Environmental application, it is usually absolute.

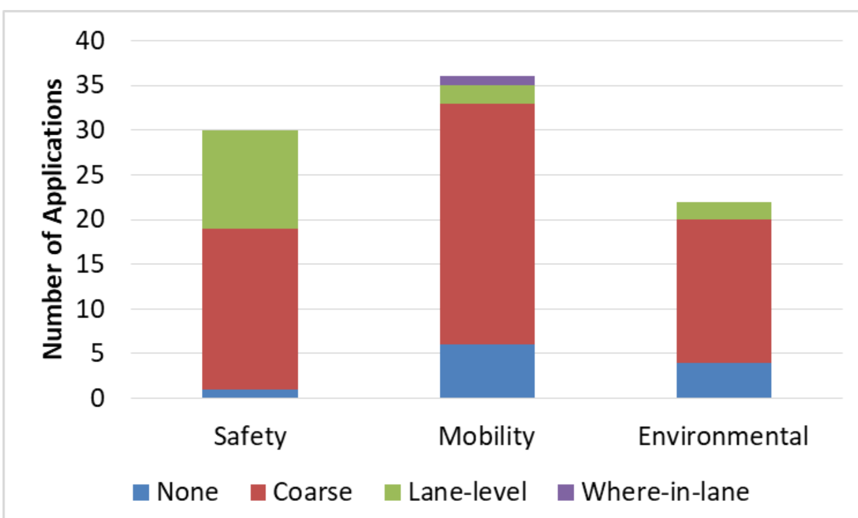

Figure 3.1: Required positioning accuracy (by application type)

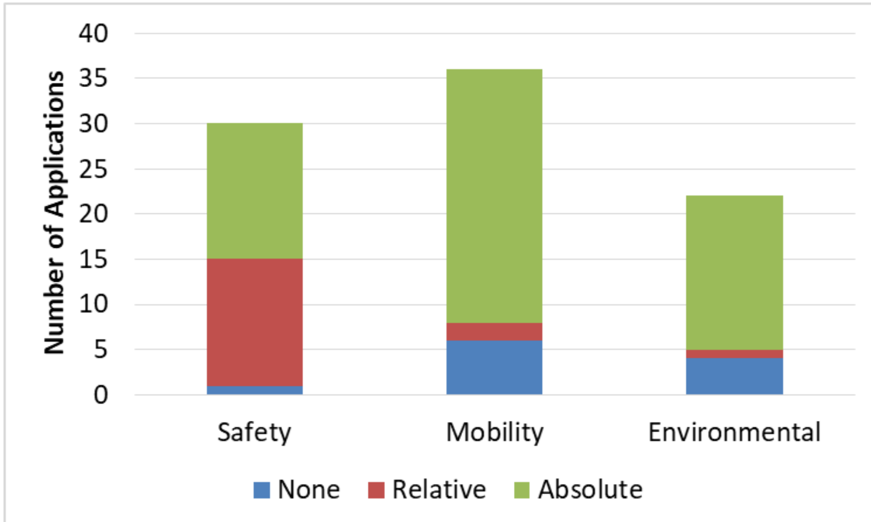

Figure 3.2: Required positioning type (by application type)

Despite the fact that lane-level accuracy enables nearly all applications, 15% of all applications benefit from where-in-lane accuracy, and many more benefit from a higher level of accuracy than is required. In fact, the "maximum benefit" accuracy is lane-level or higher for 80% of the applications. Figure 3.3 shows the distribution of required vs. "maximum benefit" accuracy. Notably, while about 10 of the applications do not require positioning, nearly all applications benefit from some form of positioning.

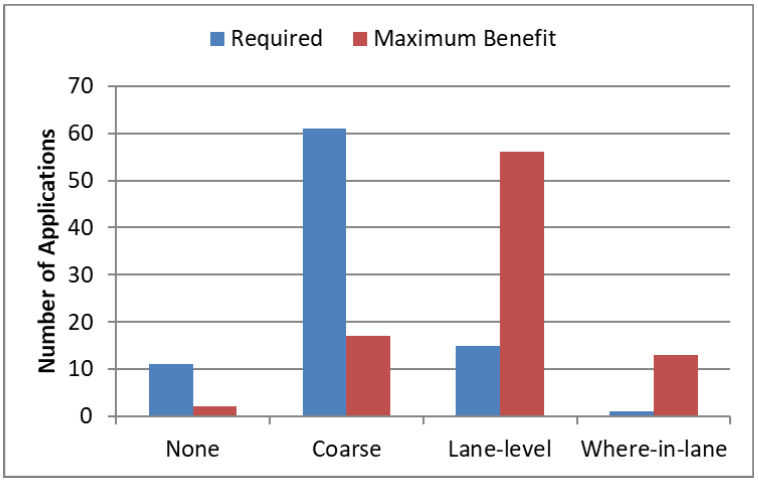

Figure 3.3. Required vs. "maximum benefit" accuracy

Figure 3.4 examines the distribution of the "maximum benefit" accuracy for each application type. It can be seen that the "maximum benefit" accuracy is lane-level or higher for all Safety applications, and for over 60% of the Mobility and Environmental applications.

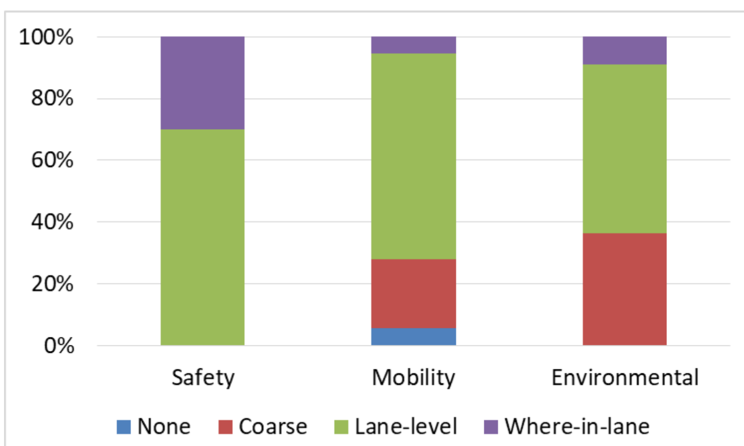

Figure 3.4. "Maximum benefit" positioning accuracy by application type

3.3.2 Safety applications

The 30 Safety applications provide information that is intended to reduce the risk of an accident. These applications address collisions with transit vehicles (Transit Safety), location-based hazards (V2I, or vehicle-to-infrastructure, Safety), and collisions with other vehicles (V2V, or vehicle-to-vehicle, Safety). Transit Safety contains only three applications. Following is a discussion of the other two groups of Safety applications, which are larger.

The 13 V2I Safety applications provide safety information based on vehicle location along the roadway. It follows that most (12 out of 13) require absolute positioning. For those applications which warn of a potential hazard ahead, such as Curve Speed Warning (approximately two-thirds of the applications fall into this category), coarse positioning is sufficient. The remaining one-third deals with collisions between vehicles and therefore requires lane-level positioning. However, all applications in this group benefit from lane-level accuracy.

Updates every 0.1 s are necessary for some of the collision prediction applications; an update interval on the order of 1 s is sufficient for the rest of the V2I Safety applications, which display information inside the vehicle once it reaches a certain area of the roadway. The positioning requirements are summarized below:

- Type: Absolute (12), Relative (1)
- Required Accuracy: Lane-level (4), Coarse (9)
- Update Interval: 0.1 s (3), 1 s (10)

The 14 V2V Safety applications are intended to prevent vehicle-vehicle crashes. Hence, nearly all require relative positioning (not absolute positioning). Similar to the V2I Safety applications, only a portion of these applications require lane-level accuracy, but all benefit from it. For most, the interval between accurate position updates must be on the order of 0.1 s, because vehicle dynamics must be closely tracked (and warnings given) in a timely manner.

- Type: Absolute (1), Relative (12), None (1)
- Required Accuracy: Lane-level (6), Coarse (7), None (1)
- Update Interval: 0.1 s (9), 1 s (4), 10 s (1)

3.3.3 Mobility applications

The 36 Mobility applications are intended to facilitate the movement of goods and vehicles. As such, they include applications to improve emergency response, ease traffic congestion, facilitate ridesharing, etc. There are 11 groups of Mobility applications.

While coarse positioning enables nearly all Mobility applications (see Figure 3.1), the "maximum benefit" accuracy is generally lane-level. Figure 3.5 shows how the "maximum benefit" accuracy varies from group to group. The first 6 groups are mostly small (1-2 applications each), so they are consolidated into the first bar. We see that lane-level is the dominant "maximum benefit" position accuracy in every bar. Also, the Traffic Network and Traffic Signals groups benefit from higher accuracy levels than the Public Safety and Transit groups.

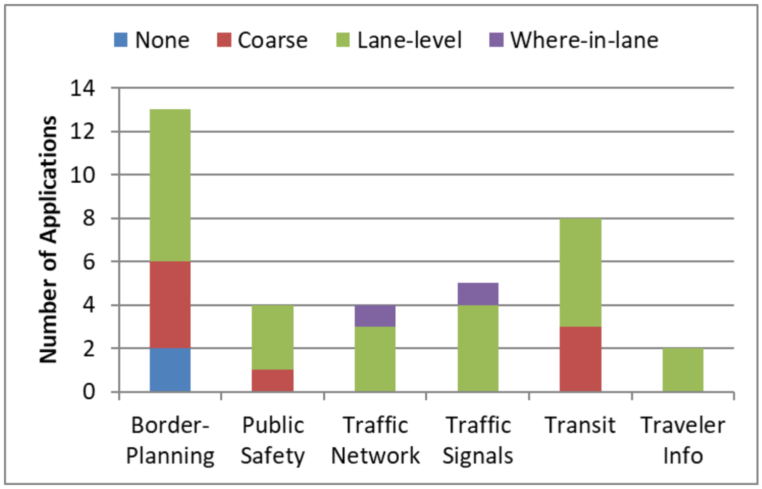

Figure 3.5. "Maximum benefit" positioning accuracy by group (mobility applications)

3.3.4 Environmental applications

The 22 Environmental applications deal with the environmental aspects of traffic: reducing energy use and emissions (the AERIS/Sustainable Travel group) and providing road weather information (the Road Weather group).

The 16 AERIS/Sustainable Travel applications range from Eco-CACC and other applications involving partial automation, to applications giving advice upon request (e.g., Dynamic Eco-Routing). In the former case, a short interval (about 0.1 s) between lane-level positioning updates is necessary, whereas in the latter case, a longer interval (on the order of 10 s) between coarse positioning updates can suffice. Therefore, the positioning requirements of this group are quite diverse. They are summarized below:

- Type: Absolute (11), Relative (1), None (4)
- Required Accuracy: Lane-level (2), Coarse (10), None (4)
- Update Interval: 0.1 s (1), 1 s (9), 10 s (5)

Approximately half of the AERIS/Sustainable Travel applications have a Mobility counterpart (for example, Speed Harmonization is the Mobility version of Eco-Speed Harmonization), in which case the positioning requirements are almost identical. The difference between the applications lies in the objective: Environmental applications primarily seek to reduce energy use and/or emissions, while Mobility applications primarily aim to lower overall travel time.

The Road Weather applications deal with weather conditions such as high winds, standing water, and flooding along the roadway. All require coarse, absolute positioning and do not gain any obvious benefits at higher levels of positioning accuracy. Though, to use probe vehicle data to accurately determine which areas of the roadway are impacted by weather conditions, position updates every second are preferable.

3.4 Summary and Discussion

Table 3.4 shows the dominant trends in the large groups (groups with 4 or more applications). While V2I and V2V Safety are the only groups in which a significant number of applications *require* lane-level positioning, it can be seen that most groups still *benefit* from lane-level positioning. The time interval between accurate position updates must be on the order of seconds for most application groups; V2V Safety's requirement is even stricter, 0.1 second. Finally, absolute positioning is required by most groups. The exceptions are V2V Safety and some of the Traffic Network applications.

Table 3.4: Summary table of application groups

		Accuracy					
Application Type	**Group**	**No Positioning**	**Coarse Positioning**	**Lane-Level Positioning**	**Where-in-Lane Positioning**	**Max. Time between Position Updates (s)**	**Positioning Type**
Safety	V2I Safety		✓	✓+		1	Abs
	V2V Safety		✓	✓+	+	0.1	Rel
Mobility	Public Safety		✓	+		1	Abs
	Traffic Network		✓	+		1	Rel/Abs
	Traffic Signals		✓	+		1	Abs
	Transit		✓	+		10/1	Abs
Environmental	Sustainable Travel		✓	+		10/1	Abs
	Road Weather		✓			1	Abs

LEGEND: ✓ REQUIRED + GAINS SIGNIFICANT BENEFITS

4 Impact of Position Uncertainty on Selected CV Applications

4.1 Overview

In the previous chapters, the vehicle positioning requirements of a variety of Connected Vehicle applications were qualitatively determined, and it was shown that affordable positioning technologies for CVs are not able to provide lane-level positioning in all environments. However, it was not clear how much of an impact substandard positioning (e.g., lower positioning accuracy than required) would have on application benefits, and existing studies of CV applications tend to neglect position uncertainty.

This chapter describes case studies that were carried out to quantify the impact of substandard positioning accuracy on CAV applications, and the resulting effect on traffic in the study area. Two state-of-the-art CAV applications were examined: 1) an environmentally-friendly application for arterial roads, called Eco-Approach and Departure at Signalized Intersections; and 2) a safety-focused highway application, High Speed Differential Warning. The applications are described in Section 2.2.

Traffic simulation was used to evaluate the impact of various levels of positioning uncertainties on these applications at the traffic level. The traffic micro-simulation package Quadstone Paramics version 6.9.3 [Quadstone Paramics] was used (see Section 2). The simulations were carried out on simulation networks that have been calibrated using real-world data collected in the field (e.g., average speed and flow at various points throughout the network). Different levels of position error were tested, and its effects on the safety, mobility, and environmental benefits of the applications were evaluated.

The rest of this chapter is organized as follows. Section 4.2 explains how position uncertainty was characterized for use in the simulations. Section 4.3 describes the simulation setup and results for the Eco-Approach and Departure application. Section 4.4 does the same for the High Speed Differential Warning application. Section 4.5 concludes the chapter with a summary and discussion.

4.2 Characterization of Position Uncertainty

Given that $\mathbf{x}_v = (x_v, y_v, z_v, c\delta t)^\top \triangleq (\boldsymbol{p}^\top, c\delta t)^\top$ represents the three-dimensional vehicle position and local clock offset with respect to GNSS time reference, a reasonable model for its estimated position is

$$\hat{\mathbf{x}}_v = \mathbf{x}_v + \boldsymbol{\eta}_v \tag{4.1}$$

where $\boldsymbol{\eta}_v$ is a random term representing the position estimation error, modeled as $\boldsymbol{\eta}_v \sim N(\boldsymbol{\mu}_v,\, \boldsymbol{\Sigma}_v)$. The covariance matrix is not necessarily diagonal, but we might initially consider $\boldsymbol{\Sigma}_v = diag(\sigma_x^2, \sigma_y^2, \sigma_z^2)$, with σ_i^2 the variance of the estimates of the i-th coordinate.

It is commonly agreed that positioning errors are adequately characterized by a Gaussian random variable, if the number of estimates is sufficiently high [Diggelen 2007]. Using the Eco-Approach and Departure application as an example, vehicle position is used to estimate the vehicle's distance to the intersection (d_{v2i}) as soon as the vehicle enters the intersection's communication range (see Figure 4.1). Each vehicle makes this estimate once for a given intersection. When considering many vehicles' estimates of this distance, it can be said that

$$\hat{d}_{v2i} \sim N(d_{v2i} + \mu_d, \sigma_d^2) \tag{4.2}$$

where $\hat{d}_{v2i}$ is a vehicle's estimated distance from the intersection; μ_d is the mean error (bias), and σ_d^2 is the variance of the error (noise). Both of these parameters depend on the errors committed on the position estimate, which propagate to $\hat{d}_{v2i}$. More precisely, we could write $\mu_d \triangleq \mu_d(\boldsymbol{\mu}_v)$ and $\sigma_d^2 \triangleq \sigma_d^2(\boldsymbol{\Sigma}_v)$.

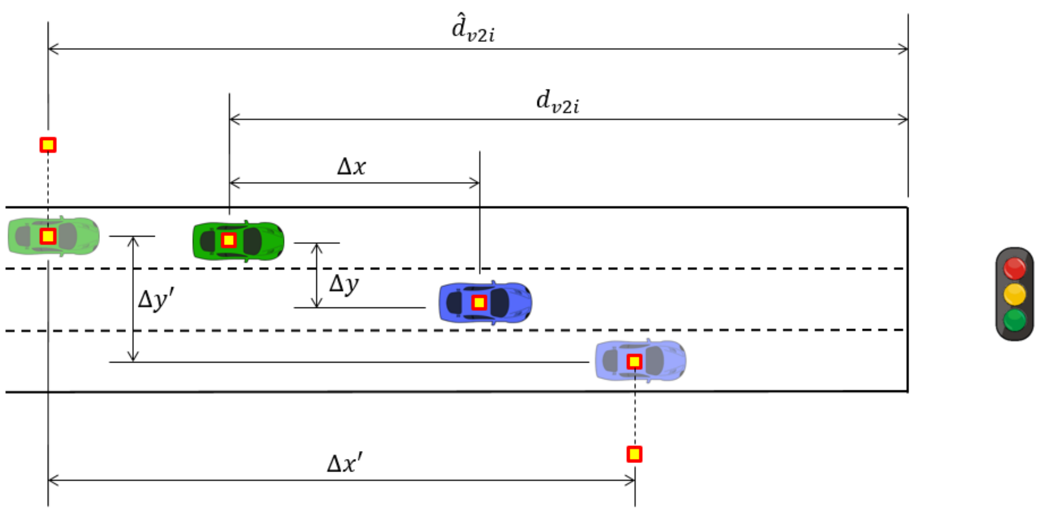

Figure 4.1: Impact of position uncertainty on estimated vehicle position

4.3 Eco-Approach and Departure at Signalized Intersections

4.3.1 Position Disturbance to EAD

As discussed in Section 4.2, longitudinal position error affects the d_{v2i} (distance to intersection) input to the EAD application. It is assumed that the vehicle is able to follow the car in front in a manner similar to a human driver, and is also able to stop at the stopbar of an intersection. This could represent: 1) a human driver who is trying to follow the speed recommended by EAD; or 2) a vehicle with automated speed control that also has a camera for detecting the stopbar and the vehicle ahead (although radar or LiDAR could also be used to detect the vehicle ahead). Lateral error could affect the application if the vehicle's lateral position is used to determine the vehicle's lane and thus which SPaT information to use (e.g., through movement vs. left turn). However, if the vehicle's route is known beforehand (which could be done by tying the driver's navigation system to the EAD application), then the vehicle's lane is not needed to determine which SPaT information to use. Therefore, we do not consider lateral position error in our analysis of this application.

Using the position error model described in Section 4.2, we assume that the bias $\mu_d = 0$, which should be true when averaged over a sufficiently high number of vehicles. Therefore, different levels of σ_d are tested. In a Gaussian distribution, 99% of observations fall within 3σ of the mean. Therefore, we test the following error levels: $3\sigma_d = \{0, 20, 40, 60, 80\}$ meters. "0 m" represents the ideal case with no position error, the "20 m" case represents some urban canyon effect, and higher levels of error represent an increasing "urban canyon" effect. The hypothesized effect of an erroneous $\hat{d}_{v2i}$ is as follows. If $\hat{d}_{v2i}$ is incorrect, the speed advice will also be incorrect (e.g., speed up instead of coast), resulting in increased energy/emissions.

4.3.2 Simulation Setup

A three-intersection signalized corridor was used for the simulation tests. The corridor is based on a section of El Camino Real in Palo Alto, California (Figure 4.2). Traffic demands and signal timing were calibrated using data collected in the field. There are three lanes in each direction, the intersection spacing varies from 200 to 500 meters and the speed limit is 40 mph. Vehicle counts and their origin-destination patterns were calibrated for the peak hour of a typical weekday morning (7:30-8:30 AM) in summer 2005. The calibrated volume-to-capacity ratio of the network is 0.77, which is considered heavy traffic.

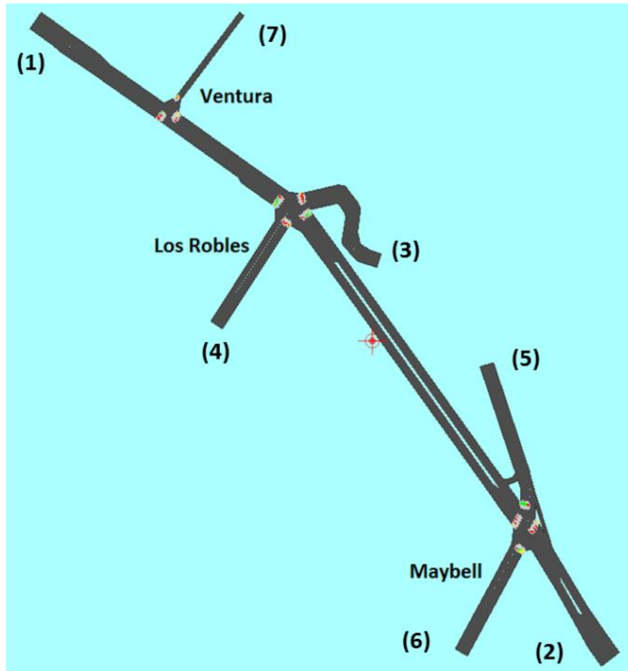

Figure 4.2. Simulation network for EAD

To account for the stochastic nature of traffic in the real world, multiple simulation runs were conducted and an average Measure of Effectiveness (MOE) was obtained for each scenario. The error bars in Figure 4.3 and Figure 4.4 represent the estimated error of the MOE, which is given by the following equation [Williams *et al.*, 2018]:

$$\epsilon = t_{\alpha/2} \frac{\delta}{\mu\sqrt{N}} \tag{4.3}$$

where $t_{\alpha/2}$ is the critical value of the t distribution at the significance level α (α = 0.05 in our study); μ and δ are the mean and standard deviation, respectively, of the MOE based on the already conducted runs; N is the number of runs; and ϵ is the error specified as a fraction of the mean μ.

4.3.3 Results

The effect of position error on EAD was tested at multiple traffic levels and penetration rates of EAD. The default setting was heavy traffic (100% of the calibrated traffic volume) and a 100% penetration rate of EAD (all vehicles are EAD-equipped). This corresponds to the “Baseline” case in Figure 4.3 and Figure 4.4. To investigate the effect in light traffic, tests were also conducted at 50% of the calibrated traffic volume. Finally, to test the effect at intermediate penetration of the technology, an EAD penetration rate of 50% was also tested.

Figure 4.3 shows how the energy savings of the EAD application change at different levels of position error. It can be seen that the Baseline energy savings start to decrease once the position error exceeds 20 m. For the other cases, the energy savings remain rather stable regardless of the position error. As Figure 4.4 shows, EAD’s effect on travel time is roughly the same whether the maximum position error is 0 (ideal case) or 20 m. At higher levels of position error, EAD’s travel time penalty increases for all three combinations of EAD penetration rate and traffic volume. Therefore, we say 20 meters is the maximum error the application can tolerate before performance starts to degrade on this particular roadway network.

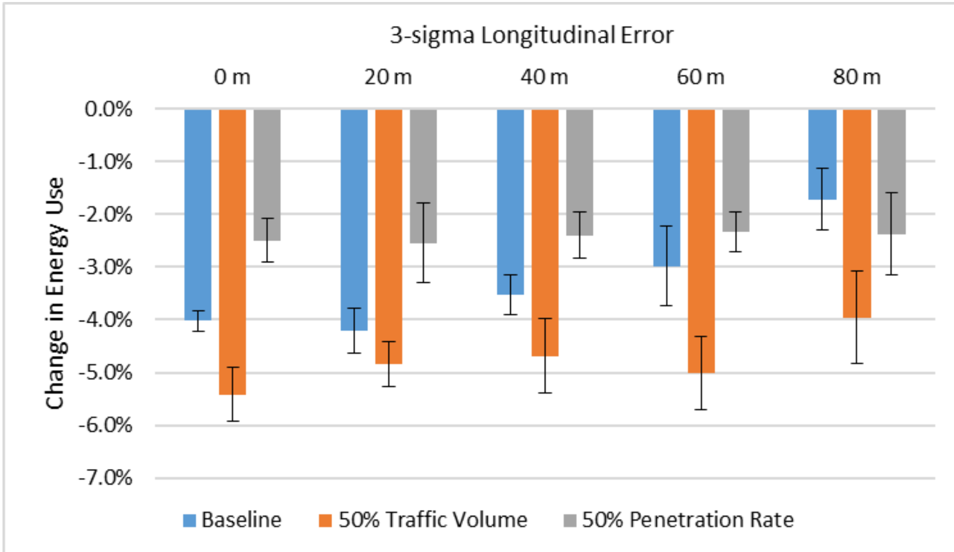

Figure 4.3: Impact of position uncertainty on energy use

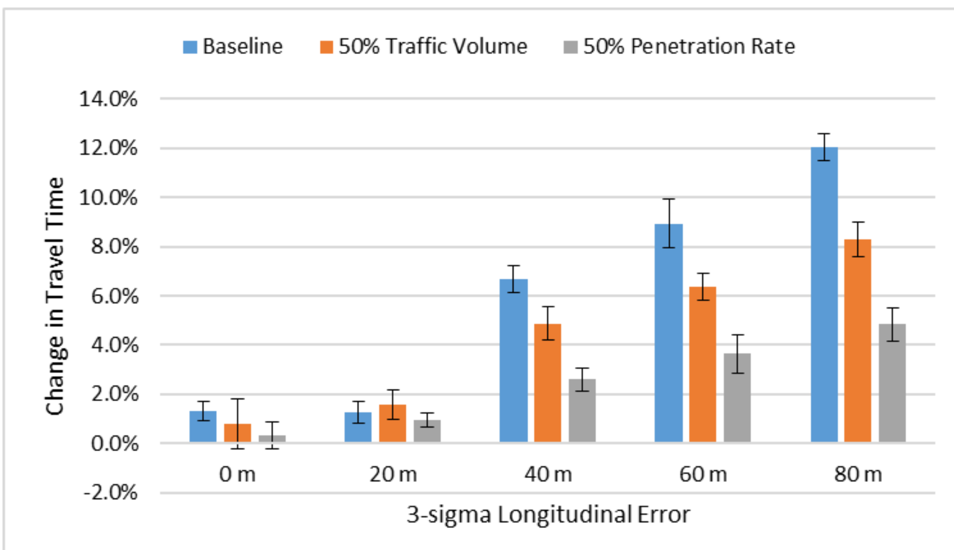

Figure 4.4: Impact of position uncertainty on mobility (travel time)

4.4 High Speed Differential Warning

4.4.1 Position Disturbance to HSDW

Longitudinal, and especially lateral, position error are hypothesized to negatively affect the HSDW application. Longitudinal error would affect the estimated distance between the Host Vehicle and Remote Vehicle (i.e., $\Delta x'$ in Figure 4.1). Lateral error could cause the estimated lane of either vehicle to be incorrect. This is quite serious, as it would result in a mistaken HSDW scenario, or an HSDW scenario not being recognized as one. Any of these outcomes would lead to incorrect HSDW logic and possibly an inappropriate driver response, which could reduce the safety benefits of the application.

Since it was hypothesized that the application would be quite sensitive to lateral position error, small lateral errors were tested. The lateral error of each communication-capable vehicle was drawn at each time step in simulation, from a Gaussian distribution having $\mu = 0$ and $3\sigma = 5\ meters$. In other words, the magnitude of error is less than 5 m, 99% of the time. The estimated lane of each communication-capable vehicle is based on the true lane, the position error, and the lane width. If the estimated position falls outside the roadway boundary, the estimated lane is set to the closest lane to that position.

4.4.2 Simulation Setup

A 15-mile highway network was used for simulation tests of HSDW. The network is based on a section of California State Route 91 East (SR-91E), extending from the Orange County Line to La Sierra Avenue in Riverside, California (see Figure 4.5). It has curved sections and 9 pairs of on-/off-ramps. The number of lanes varies from 4 to 6; the speed limit is 65 mph. The road segment is highly utilized. Traffic demands for this network were calibrated based on a typical weekday morning in the summer of 2006 [Boriboonsomsin and Barth, 2006].

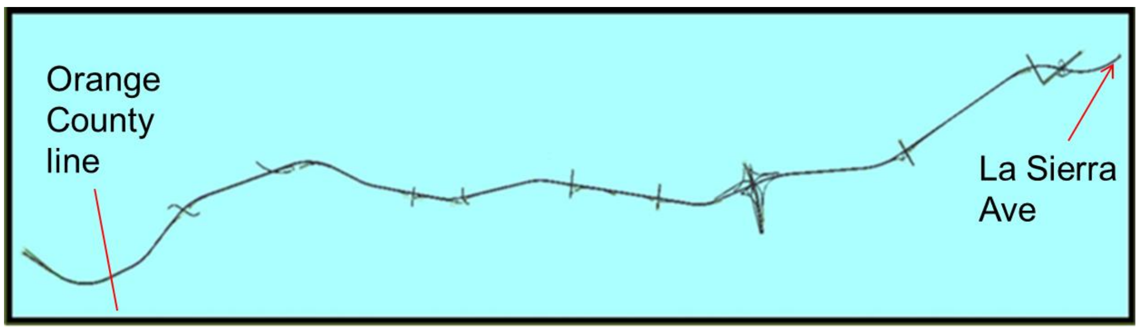

Figure 4.5: Simulation Network for HSDW (SR-91E)

Since HSDW is primarily a safety application, the chosen Measure of Effectiveness (MOE) was a surrogate safety metric, the average number of potential rear-end conflicts per vehicle. This is calculated as the total number of potential rear end conflicts divided by the total number of vehicles. 10 runs were made for each combination of traffic volume level and DSRC penetration rate. The error associated with the MOE for each configuration was obtained using equation (4.3). The error is represented by the error bars in Figure 4.6 - Figure 4.9.

4.4.3 Results

The position disturbance to HSDW was tested at two traffic volumes and two application penetration rates. The traffic volumes tested were medium (25,000 vehicles) and heavy (32,000 vehicles). These correspond to Levels of Service D (transitional flows) and E (unstable flows), respectively, for that network [HCM 2010]. In this study, the penetration rate of HSDW was fixed at 9% of DSRC-equipped vehicles (to represent the market share of an automobile manufacturer that chooses to include the HSDW application on its DSRC-equipped vehicles), and DSRC penetration rates of 20% and 100% were tested.

Chronologically speaking, a DSRC penetration rate of 20% will be reached before 100%. When the penetration rate is 20% and the traffic volume is medium, neither the HSDW-equipped nor the other vehicles have a significant change in the number of conflicts (see Figure 4.6), even with perfect positioning. In the presence of position error, the average number of conflicts increases for HSDW-equipped vehicles, but as the error bars show this change is not statistically significant.

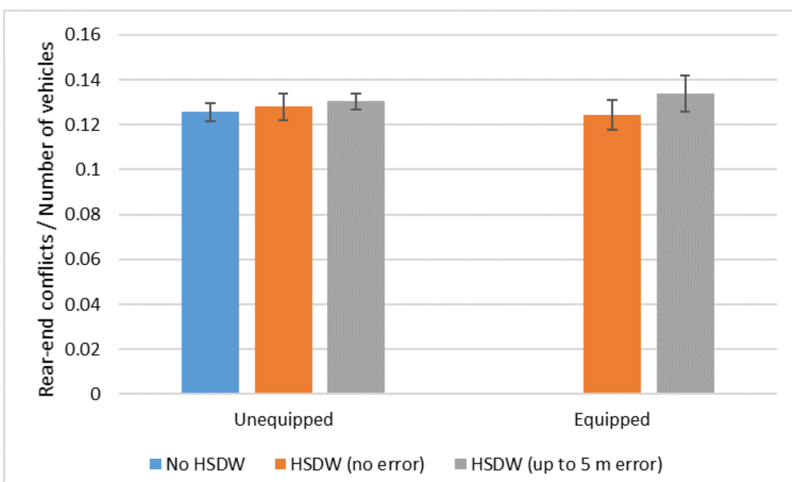

Figure 4.6: HSDW results (Medium traffic, 20% DSRC-equipped)

When the traffic level is heavy (still 20% penetration of DSRC), HSDW provides a large safety benefit for HSDW-equipped vehicles (see Figure 4.7). With perfect positioning, HSDW cuts the number of conflicts in half. However, adding lateral errors up to 5 m is sufficient to decrease the safety benefit substantially (from -50% conflicts to -30%).

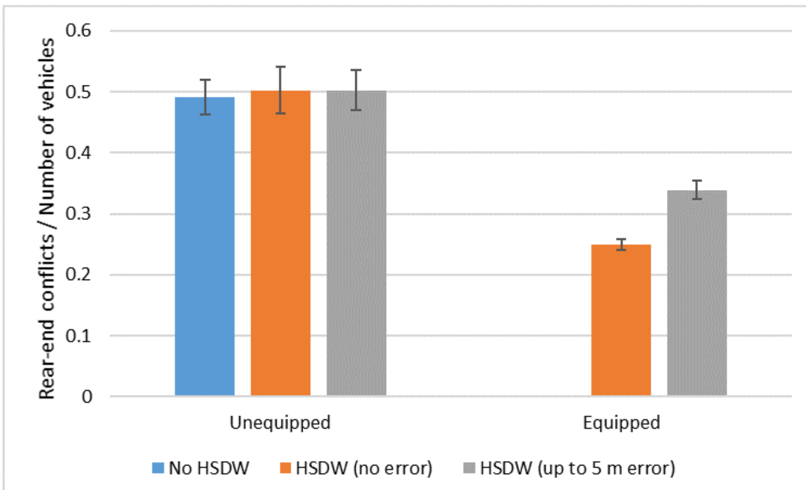

Figure 4.7: HSDW results (Heavy traffic, 20% DSRC-equipped)

When the penetration rate of DSRC is 100%, the results for medium traffic volume are similar to the results for a 20% DSRC penetration rate (see Figure 4.8). In heavy traffic (Figure 4.9), HSDW with perfect positioning cuts the number of conflicts by about 60% for HSDW-equipped vehicles. However, when the simulated position error is present, the reduction in conflicts becomes only 30%.

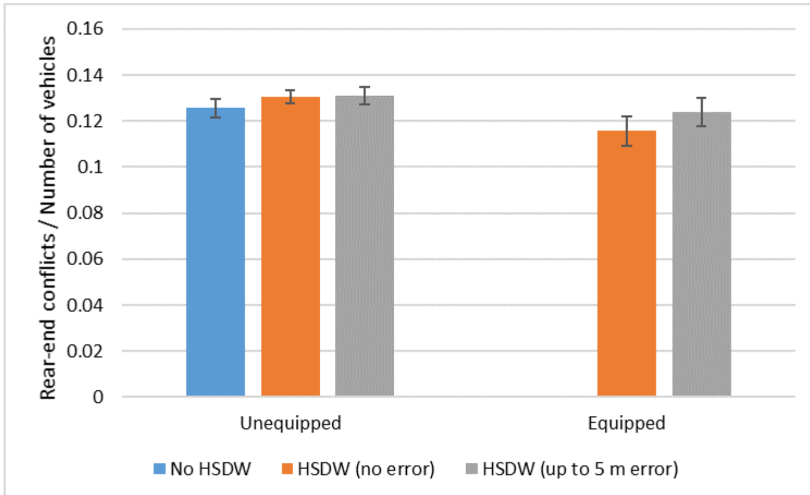

Figure 4.8: HSDW results (Medium traffic, 100% DSRC-equipped)

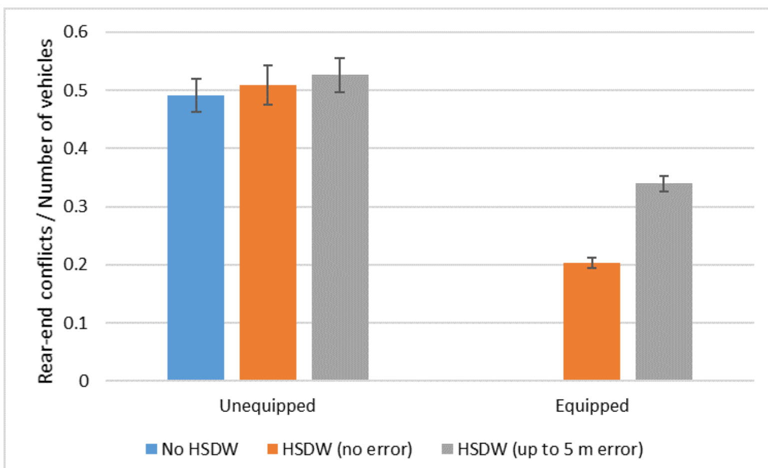

Figure 4.9: HSDW results (Heavy traffic, 100% DSRC-equipped)

4.5 Summary and Discussion

In this chapter, a simple position error model was developed and used to test the effect of different levels of position error on two different Connected Vehicle applications: Eco Approach and Departure at Signalized Intersections and High Speed Differential Warning. Traffic simulations were carried out at various traffic levels and technology penetration rates.

The Eco-Approach and Departure application examined in this chapter only requires vehicle position for the “distance to intersection” input to the application. Position errors up to 20 m did not noticeably affect system performance, at the traffic volumes and application penetration rates tested. This corresponds to Chapter 3’s finding that this application requires only coarse positioning accuracy. However, position errors greater than 20 m always worsened system-wide mobility, and sometimes increased energy use as well.

The HSDW application requires knowledge of vehicle lane to function properly, and therefore requires lane-level positioning accuracy. The experimental findings in this chapter confirm this: even errors bounded by 5 m (a lane is typically 3-3.5 m wide), in the lateral direction, caused application benefits to drop significantly in heavy traffic, whether the percentage of communication-capable vehicles was 20% or 100%. The particular position error model used may be considered unrealistic in that values were randomly drawn from a Gaussian distribution. This means that, theoretically, it was possible for the error to jump a large distance (the maximum would be from +5 m to -5 m) in one time step. In reality, the GNSS receiver’s Kalman filter would probably prevent such a rapid deviation in the lateral direction. However, the distribution is also narrow ($\sigma = 1.67\ m$) compared to that of typical urban canyon position error ($\sigma \approx 10\ m$). These results demonstrate the necessity of: 1) using sufficiently accurate position information as input to these applications, and/or 2) modifying the applications so that they can accommodate some position error.

5 Position Error-Tolerant Cooperative Merging Application

5.1 Overview

Cooperative merging is a promising CV application for improving the safety, mobility, and/or environmental impact of traffic at merging areas, such as those at roundabouts and highways. As described in Section 2.2.3, a variety of strategies for cooperative merging have been developed. However, none of these takes into account possible errors in the vehicles' position, and many of them assume 100% of vehicles to be equipped with the hardware and software necessary for the merging strategy. This will not be the case for quite some time, except perhaps at traffic facilities dedicated to CAVs. Studies that do examine intermediate penetration rates of CAVs tend to show benefits only when the penetration rate is 50% or higher [Zhao *et al*., 2018; Rios-Torres and Malikopoulos, 2018].

This chapter presents a set of cooperative merging strategies that provides safety, mobility, and environmental benefits to the traffic stream, even at penetration rates as low as 20% in some cases. Two of the strategies are also able to accept position errors typical of an urban canyon. It is shown that adjusting the application (by increasing the inter-vehicle spacing) leads to increased benefits under certain circumstances.

The rest of this chapter is organized as follows. Section 5.2 describes the development of a model for GNSS position error in an urban canyon based on real-world data. Section 5.3 describes the developed cooperative merging strategies. Simulation tests of the strategies under varying conditions are described in Section 5.4. The chapter ends with a summary and discussion.

5.2 Development of a GNSS Position Error Model

In order to implement realistic position error in simulation, we developed a model for position error based on real-world data. Position data were collected using GNSS positioning systems of a similar grade to those used by Connected Vehicles in current deployments [Hailemariam *et al*., 2018]. The receivers were first tested under open-sky conditions to verify their open-sky accuracy. Then, they were mounted on a vehicle and driven through an urban canyon (downtown Los Angeles, California), and the lateral position error of each receiver was calculated.

5.2.1 Data Collection

Data from three single-frequency GNSS receivers were collected. The receivers consisted of one u-blox NEO-7P and two NEO-M8P receivers. The NEO-7P is a single-constellation (GPS) receiver, whereas the NEO-M8P is a multi-constellation (GNSS) receiver. The NEO-7P utilized WAAS corrections, and one of the NEO-M8P receivers utilized RTCM corrections to enable its RTK mode.

All three receivers were connected to a NEO-M8P's patch antenna using a GPS splitter. The antenna was centered on top of the test vehicle, and RTCM corrections were downloaded in the test vehicle using a Netgear AirCard 770S 4G LTE mobile Wi-Fi hotspot.

5.2.2 Open-Sky Test

Two two-hour static tests were first conducted to characterize the open-sky position accuracy of each receiver. Average position error was calculated as the distance of each measured point from the actual location of the receiver. Table 5.1 shows the test results. As expected, the receiver with RTCM corrections has the highest accuracy due to its RTK mode. The receiver with WAAS corrections is the next most accurate, followed by the receiver with no corrections. Dynamic (i.e., test vehicle is moving) data from the receivers were also examined, and the measured positions were observed to fall in the correct lane on Google Earth.

Table 5.1: Static open-sky test results

	Avg. Position Error [m]		
Test location	No corrections	WAAS	RTCM
Riverside	1.43	1.23	0.06
Los Angeles	1.25	1.12	0.15

5.2.3 Urban Canyon Test

The urban canyon dynamic test took place in downtown Los Angeles, California. For this test, an additional piece of equipment was used: a forward-facing camera, attached to the inside of the windshield, recorded which lane the vehicle was traveling in. The test vehicle was driven continuously for approximately 25 minutes on each of three test routes. The first two routes had skyscrapers adjacent to the roadway (the first route is shown by the white line on Figure 5.1). The third route did not. Therefore, we classified the first two routes as "deep" urban canyons, and the third route as a "medium" urban canyon.

Figure 5.1 shows data from the first two runs on the first deep urban canyon route. The red trace shows the path formed by position measurements from the receiver with RTCM corrections; blue is the receiver with WAAS corrections; and green is the receiver without any corrections. The “ground truth”, or reference, trajectory is shown in white. It was traced on Google Earth using the vehicle’s lane, which was recorded by the camera mounted on the vehicle.

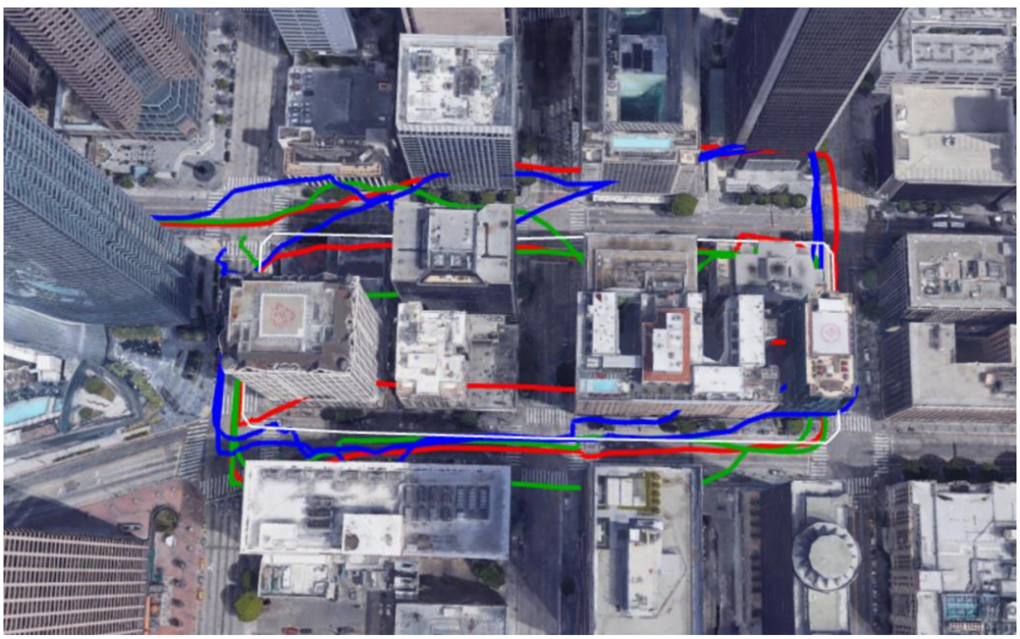

Figure 5.1: GNSS tracks from the first two runs on a deep urban canyon route (red: RTCM corrections, blue: WAAS corrections, green: no corrections, white: truth)

Lateral position error was calculated as the shortest distance from each GNSS position to the reference route. Figure 5.2 shows the error vs. time plot for all three receivers on the third (medium urban canyon) route. It can be seen that the lateral position error rarely exceeds 20-30 m. The data from all three routes were aggregated together, and it was found that the position error tends to follow a half-normal distribution (half-normal rather than normal since only the magnitude of the error was measured). This is shown in Figure 5.3, where the blue histogram shows the actual data from each receiver, and the red line is the half-normal fit. $\mu = 0$, and σ is listed in the title of each plot. The function fits fairly well in all three cases.

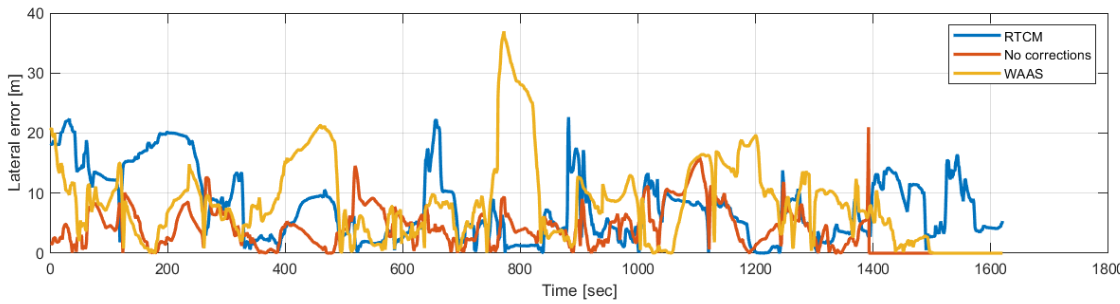

Figure 5.2: Lateral error vs. time on the medium urban canyon route

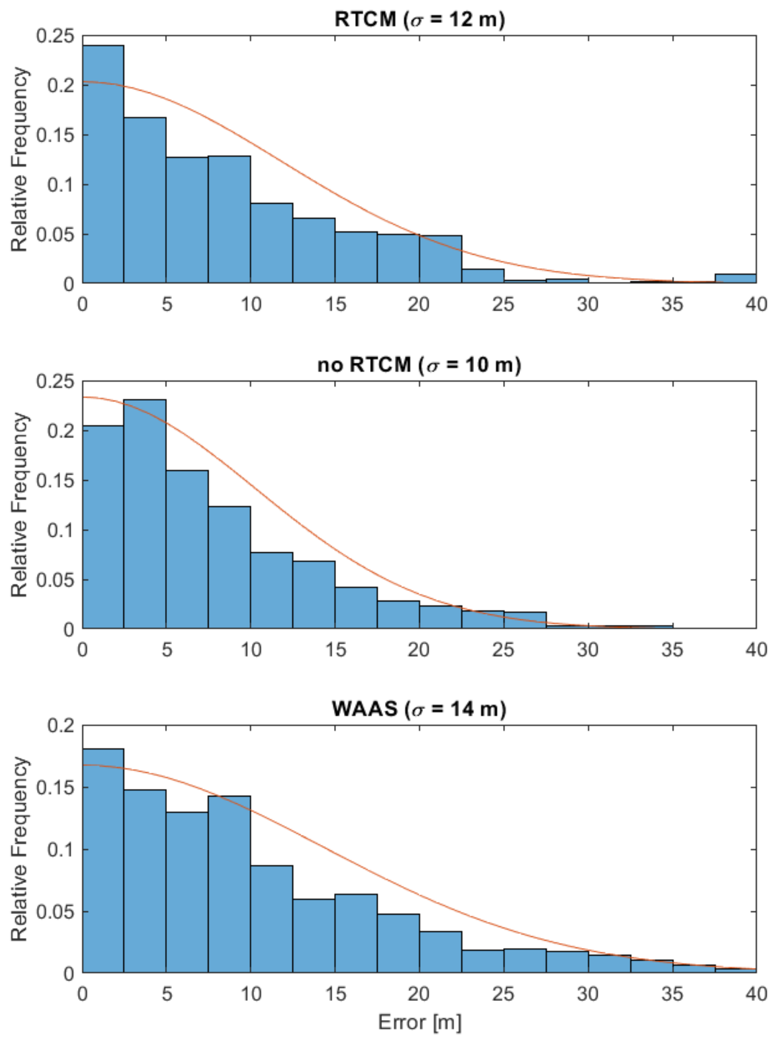

Figure 5.3: Actual error distributions and half-normal fit

When modeling position error for an application like that uses a vehicle's measured position continuously (e.g., cooperative merging), the error should behave realistically. If it is simply drawn from a distribution with the parameters above, the error may change by a large amount in a single time step, which is not realistic. The same real-world experimental data showed that the amount of position error changed more gradually, typically at a rate of 2 m/s or less (see the blue distributions in Figure 5.4). A logistic distribution was fit to these data (red histograms).

The logistic distribution can be represented as $L(\mu, s)$ with probability density function given by

$$f(x;\ \mu, s) = \frac{e^{-\frac{x-\mu}{s}}}{s(1 + e^{-\frac{x-\mu}{s}})^2} \tag{5.1}$$

where μ is the mean (the distribution is symmetric) and s is a scale parameter proportional to the standard deviation. The red histograms represent a logistic distribution with $s = 0.3\ m/s$. A logistic rather than normal distribution was used because a logistic distribution has heavier tails (higher kurtosis). Even so, Figure 5.4 shows that the experimental data have even higher kurtosis than the fitted logistic distribution.

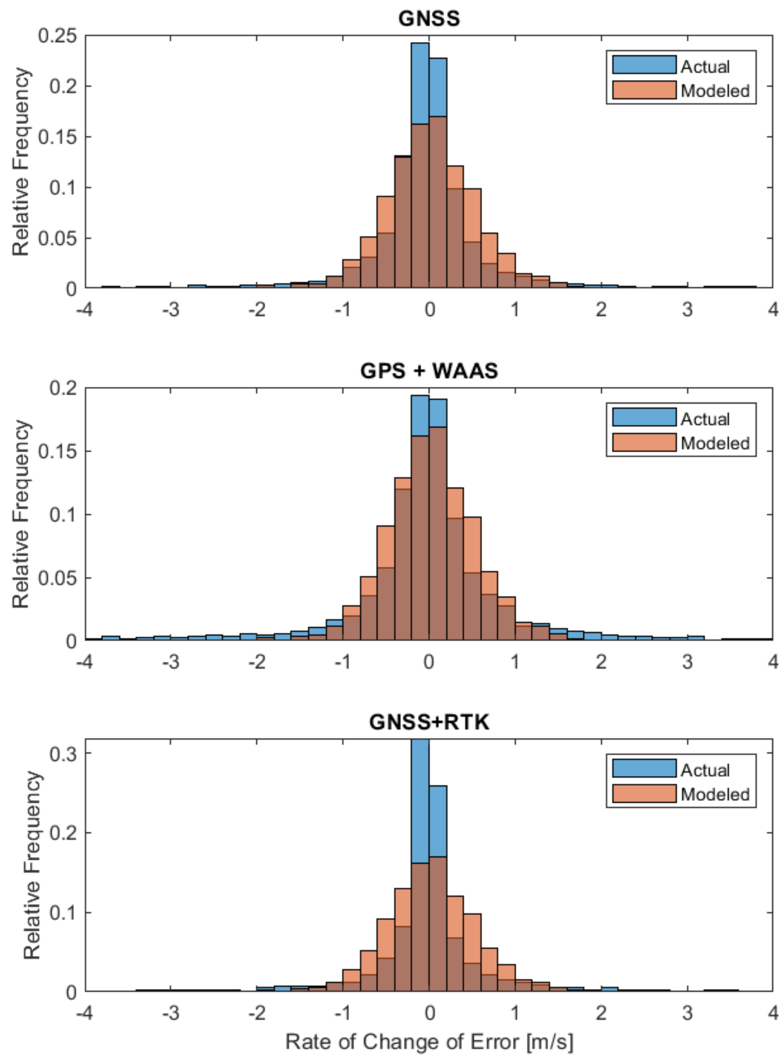

Figure 5.4: Rate of change of lateral position error in the urban canyon

5.2.4 Real-Time Position Error Model

Error in the lateral (cross-street) direction is typically 1-5 times larger than error in the longitudinal (along-street) direction [Groves, 2011]. Since in the cooperative merging application we are only dealing with longitudinal position error, we had to convert it from lateral error. This was done, albeit approximately, by dividing the parameters of the error distributions (which corresponded to lateral error) by 2.

Position error was modeled in the simulation as follows. When a vehicle enters the simulation network, its initial longitudinal position error, which translates to error in the “distance to start of merge zone” input to the application, is randomly drawn from a Gaussian distribution:

$$(\hat{d}_{v2m})_{t=0} \sim N(\,(d_{v2m})_{t=0}\,, \sigma_d^2) \qquad (5.2)$$

where $t = 0$ indicates the time when the vehicle enters the control zone, $(d_{v2m})_t$ is the distance the vehicle still has to travel to reach the start of the merge zone (as of time *t*), and σ_d is the standard deviation of the longitudinal position error. For this simulation network, we set $\sigma_d = 5$ meters. In the real world, this value would vary by location and time.

Subsequently, the position error is allowed to change at a gradual rate, as indicated in the following equation:

$$(\hat{d}_{v2m})_t = (\hat{d}_{v2m})_{t-T.S.} + T.S. \times L(\mu, s) \qquad (5.3)$$

where $(\hat{d}_{v2m})_t$ is the estimated remaining distance to the start of the merge zone at time t, $T.S.$ is the length of a simulation time step (0.1 second), and $L(\mu, s)$ is the logistic distribution. We set $\mu = 0$ and s = 0.15 m/s.

5.3 Cooperative Merging Strategies

Three cooperative merging algorithms, each corresponding to a different testing scenario, were developed. In the first scenario, vehicle positions are perfectly known (in the real world, submeter accuracy should suffice). In the second scenario, the position error is representative of a typical urban canyon, and the merging algorithm is modified in two ways so that the algorithm can still function, and so as to lessen the negative impact of position error. In the third scenario, the position error is the same, but the merging algorithm is further modified so that there is increased spacing between vehicles. All three were tested under the same conditions. The application makes several assumptions, which are listed below:

- If there is a vehicle ahead within 50 m, the distance to it, and its relative speed, are known (this information could be provided by a ranging sensor, such as camera). This assumption is considered reasonable in light of the fact that 99% of new cars in the U.S. will require an automated emergency braking (AEB) system by 2022. Such a system needs to know the above information.
- The vehicle’s lane is known (this could be provided by a camera that identifies lane markings). This information is required so that mainline vehicles know whether they are in the outermost lane of the highway, in which case their application is active.
- Road geometry in the control zone is known—so that the distance to merge point can be calculated based on the vehicle’s current position.

5.3.1 Base Algorithm

Cooperative merging requires communication between vehicles, directly (V2V communication) and/or indirectly via the infrastructure (V2I communication). In the literature, vehicle communication and control generally occurs upstream of the merging area and sometimes within the merging area as well. In our scenario, vehicle control is done only upstream of the merging area ("merge zone"); we refer to the area within which vehicles are controlled as the "control" zone. This zone extends 375 m upstream of the start of the merge zone (see Figure 5.5).

Cooperative merging can be broken down into two distinct tasks: 1) determination of vehicle sequence (in which order the vehicles should merge), and 2) control of vehicle dynamics [Wang *et al.*, 2018]. These tasks are carried out for all application-equipped vehicles within the control zone, at every time step. Regarding (1), the on-ramp is sufficiently long that by the time ramp vehicles enter the control zone, most of them have accelerated to the free-flow speed on the mainline. Therefore, vehicle sequence is determined by distance to the start of the merge zone: whichever vehicle is closer, merges first. The sequence is updated in real-time, so that if a vehicle is slowed down by other vehicles in front, it may be pushed back in the sequence.

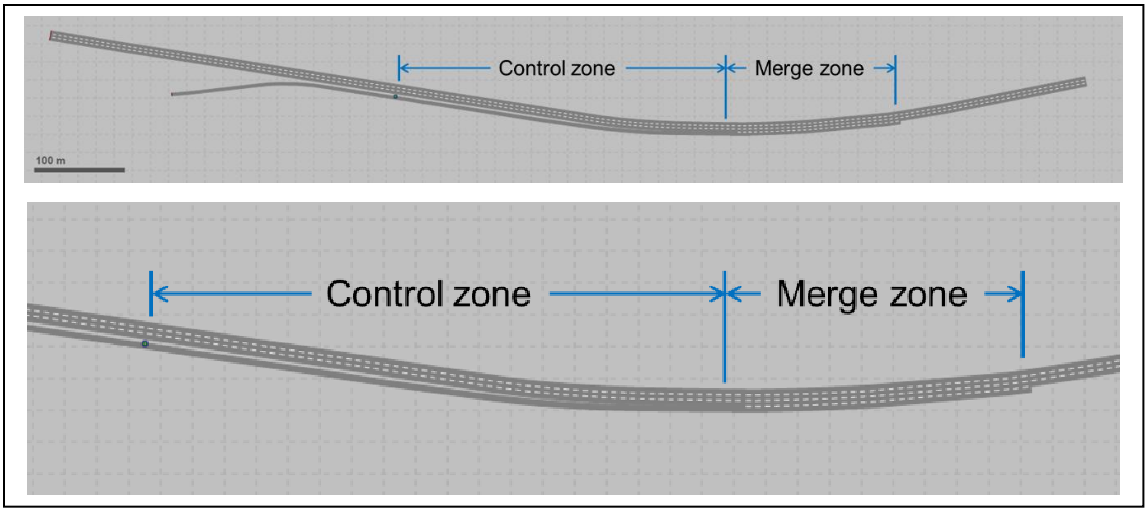

Figure 5.5: Simulation network for Cooperative Merging

Based on the vehicle sequence, an application-equipped vehicle follows a speed/gap control strategy which is adapted from that described in [Shladover *et al.*, 2012]. If the vehicle is first in the sequence, it follows speed control (tries to follow the speed limit). Otherwise, the vehicle uses gap control, trying to maintain a desired gap from the vehicle ahead of it in the sequence. The acceleration prescribed by speed control is

$$a_{sc} = bound(-0.4(v - v_d), 2, -2) \tag{5.4}$$

where a_{sc} is the acceleration in m/s^2, v is the vehicle speed in m/s, v_d is the desired speed (set to the speed limit), and the "bound" function is defined as follows.

If $y = bound(x, x_{ub}, x_{lb})$, then

$$y = \begin{cases} x_{ub}, & if\ x > x_{ub} \\ x_{lb}, & if\ x < x_{lb} \\ x, & otherwise \end{cases} \tag{5.5}$$

The acceleration prescribed by gap control is

$$a = bound(\dot{s} + 0.25(s - s_d), a_{sc}, -2) \tag{5.6}$$

$$s_d = T_d v \tag{5.7}$$

where s is the spacing between the two vehicles (in meters), s_d is the desired spacing, T_d is the desired time headway (seconds), and $\dot{s}$ is the rate of change of the spacing.

This strategy may be considered somewhat optimistic for current ACC systems because it ignores the half- to full-second lags associated with processing sensor signals. However, recently proposed ACC strategies compensate for this delay by predicting the future state based on current sensor measurements [Bekiaris-Liberis *et al.*, 2017; Wang *et al.*, 2018]. Therefore, we use this delay-less model in our simulation, assuming that by the time vehicles are able to automatically follow the merging advice, they will be equipped with these advanced ACC systems.

If speed control is used, then $a = a_{sc}$. The final acceleration used by the vehicle is the minimum of a and the original acceleration prescribed by VISSIM's car-following model. The reason for this is to ensure that the vehicle does not crash into the one ahead of it, which may not be application-equipped. This could represent the actions of human driver intervention or an automatic emergency braking (AEB) system.

5.3.2 First Modification for Position Error

Position error affects the merging algorithm in several ways. First, it introduces error into the spacing term of the gap control, causing vehicles on different lanes to not line up properly. Second, it may alter the vehicle sequence. Figure 5.6 illustrates a situation where both of these problems are present. Vehicle 1 is, in reality, ahead of

Vehicle 2; however, the measured positions of the vehicles (represented by the grayed-out vehicles) make it seem as if Vehicle 2 is ahead of Vehicle 1. As a result, Vehicle 1 may decelerate when in fact Vehicle 2 should either decelerate or maintain constant speed. As a result, the vehicles will come closer together in terms of their longitudinal position, which runs contrary to the goal of the merging algorithm.

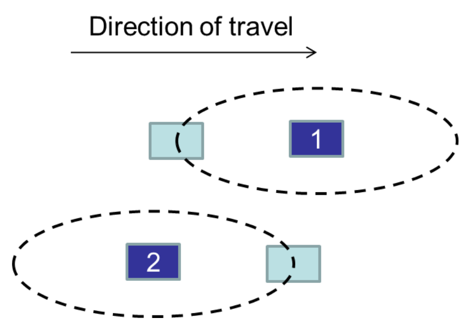

Figure 5.6: Example effect of error on vehicle position measurements

If the two vehicles are in the same lane, this problem can be solved simply by the following vehicle using its ranging sensor to obtain the distance and relative speed of the leading vehicle. This is one of the modifications made for this second algorithm.

Another modification was necessary. The above problems simply reduce the efficiency of the merging algorithm. A more critical problem was also observed to arise as a result of position error. When position error caused mistakes in the vehicle sequence, traffic sometimes came to a complete stop as a result of a situation like that illustrated in Figure 5.7. The numbers show the vehicle sequence as determined from position measurements. Using the original merging algorithm, if Vehicle 2 is forced to slow down by a vehicle ahead, Vehicle 3 will follow suit (because it is using gap control to "follow"

Vehicle 2). Vehicle 1 is then forced to decelerate (and Vehicle 2 decelerates to "follow" it), leading to a loop of deceleration until all 3 vehicles come to a complete halt.

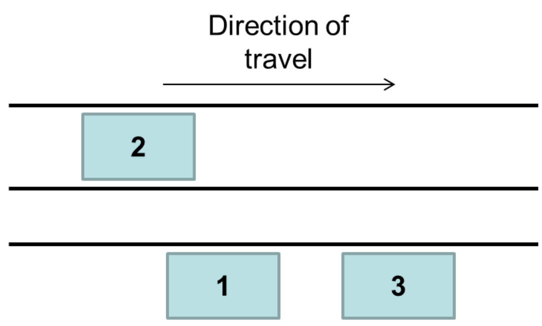

Figure 5.7: Example lock-up scenario

The chosen solution for this problem was to add a condition for gap control: if there is no vehicle ahead for a certain distance (we selected $3s_d$), the vehicle defaults to speed control. In this way, vehicles will cease decelerating due to gap control, once they fall behind the rest of the traffic by a distance of $3s_d$.

5.3.3 Second Modification for Position Error

The above modified merging strategy was also adjusted as follows, to see if the adjustment would improve algorithm performance. If the application-equipped vehicle is "following" a vehicle on a different lane, the desired spacing s_d will be increased by $2\sigma_d$, which is two times the standard deviation of the local position errors. In this case, $\sigma_d = 5\ m$, so s_d was increased by 10 m.

5.4 Simulation Tests

All three cooperative merging strategies were tested in simulation. The traffic microsimulation package VISSIM was used. The geometry of the simulation network is based on the area of the CA-91E freeway where it is joined by the Serfas Club on-ramp in Corona, CA (see Figure 5.5). In the simulation network, the number of highway lanes was varied from 2 to 3 to investigate the effect of different number of lanes. The vehicle inputs used for each case are given in Table 5.2. Different penetration rates of each merging strategy were tested. 10 simulation runs, each one simulated hour long, were conducted for each merging strategy, penetration rate, and number of highway lanes.

Table 5.2: Vehicle inputs

	Vehicle Demand [vph]	
Number of Highway Lanes	Highway	Ramp
2	4400	800
3	6600	1200

Second-by-second vehicle trajectory data were collected and used to calculate safety, mobility, and environmental metrics for the network. Time-to-collision (TTC) is a safety indicator defined as the time required for two vehicles to collide, if they continue on their current courses and speeds. It is generally agreed that a TTC of less than 1.5 seconds is in the critical, rather than normal, driving regime [Grayson, 1984; van der Horst, 1990; Gettman *et al*., 2008]. Therefore, the number of occurrences with TTC < 1.5 seconds was used as the safety metric.

The mobility metric was average speed, defined as

$$\bar{v} = \frac{VMT}{VHT} \tag{5.8}$$

where $\bar{v}$ is the average speed (mph), VMT = total vehicle miles traveled, and VHT = total vehicle hours traveled. The environmental metrics were energy use and amount of various pollutant emissions (CO, CO_2, NO_x, HC, and $PM_{2.5}$), all calculated using the MOVES model.

Level of Service (see Section 2.4) of the highway was also determined, based on vehicle density just upstream of the start of the merge zone (see Figure 5.5). Density was computed from 5-minute average speed and flow measurements as follows:

$$Density\ (\frac{veh}{mi}) = \frac{Flow\ (\frac{veh}{hr})}{Speed\ (\frac{mi}{hr})} \tag{5.9}$$

5.4.1 Two-Lane Highway

Figure 5.8 shows the level of service over time on the two-lane highway when no vehicles are using any cooperative merging strategy. The horizontal lines indicate the density thresholds between different levels of service. Each non-horizontal line represents a simulation run. In this scenario, it can be seen that the Level of Service starts around D-E and then rises to F, usually by the 25-minute mark. When 100% of vehicles are equipped with the cooperative merging strategy with perfect positioning, much more time is spent in LOS D-E rather than LOS F, as can be seen in Figure 5.9.

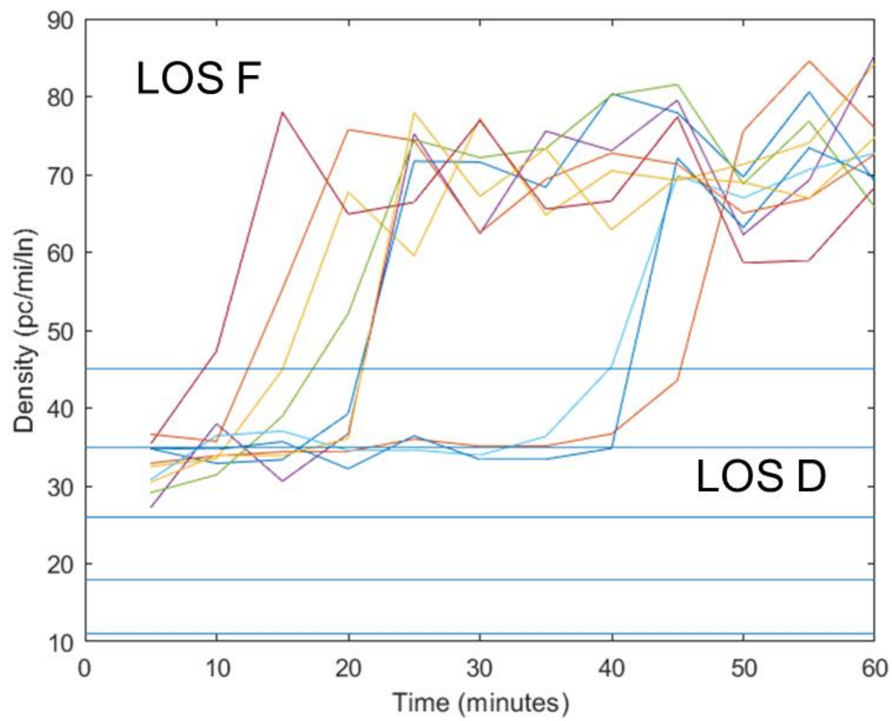

Figure 5.8: Level of Service on the 2-lane highway (0% equipped)

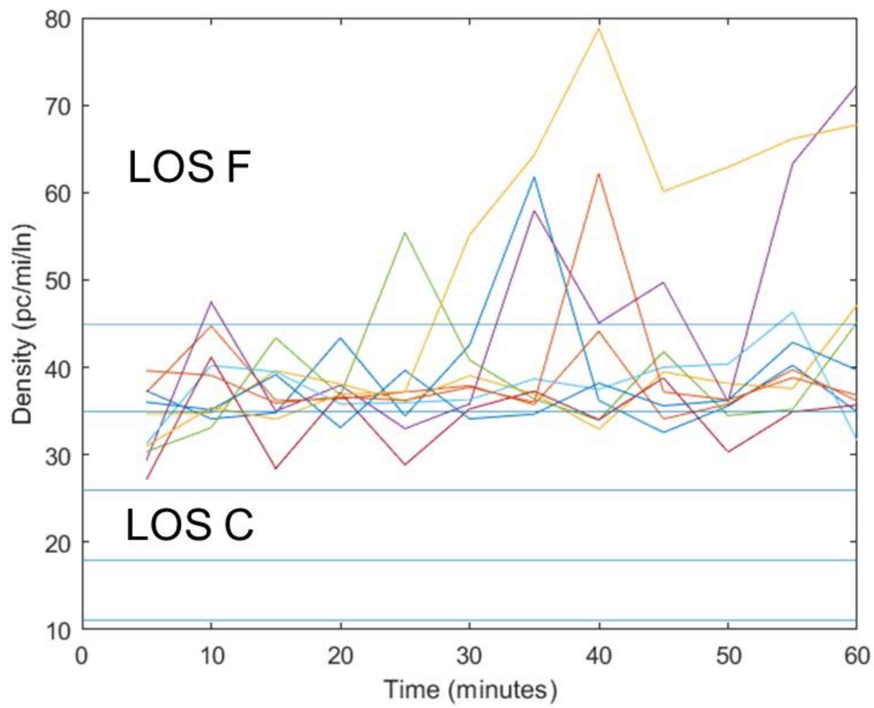

Figure 5.9: Level of Service on the 2-lane highway (100% equipped)

The difference in LOS (congestion levels) translates to the mobility results shown on Figure 5.10, which shows that equipping 100% of vehicles with the merge application increases average speed on the network by about 80% (from 30 mph to 55 mph). As expected, the mobility benefit increases with the percentage of equipped vehicles, for the first merging strategy (perfect positioning). When typical urban canyon position error is present, the benefits are not as high. Increasing the spacing between vehicles appears to help at 100% penetration rate but not at the lower penetration rates.

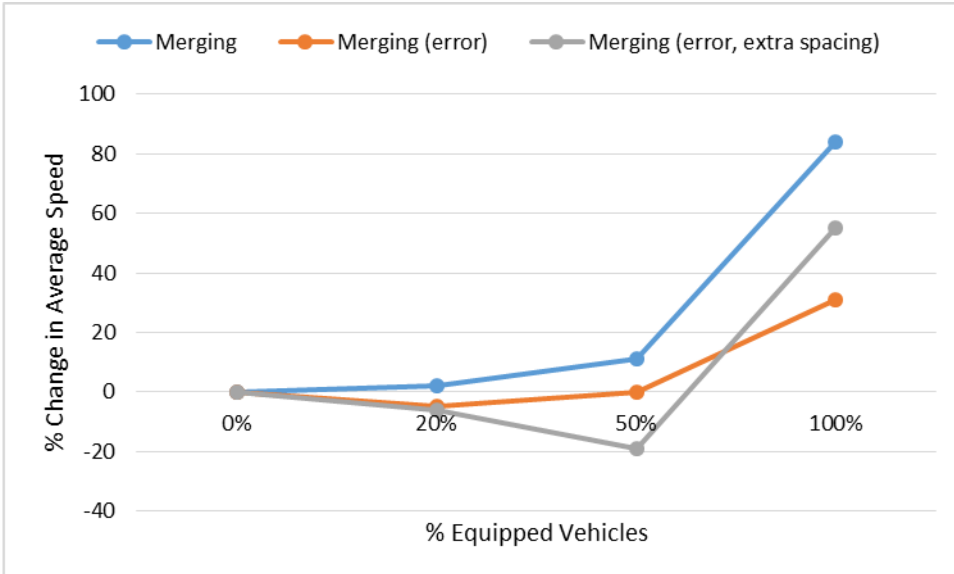

Figure 5.10: Mobility results for the 2-lane highway

Figure 5.11 shows the effect on network-wide safety, in terms of the number of potential conflicts (occurrences of a time-to-collision (TTC) of less than 1.5 seconds), in the second-by-second trajectory data. These results are similar to the Mobility ones, in that the perfect positioning case performs best. It can be seen that the number of conflicts is greatly reduced, even if only 20% of vehicles are equipped. For the "Merging (error)" case, it appears that a penetration rate of 50% is sufficient to see substantial safety benefits. Although the directly measurable effect on mobility at this penetration rate is small, mobility may see indirect benefits due to the lowered chance of a crash.

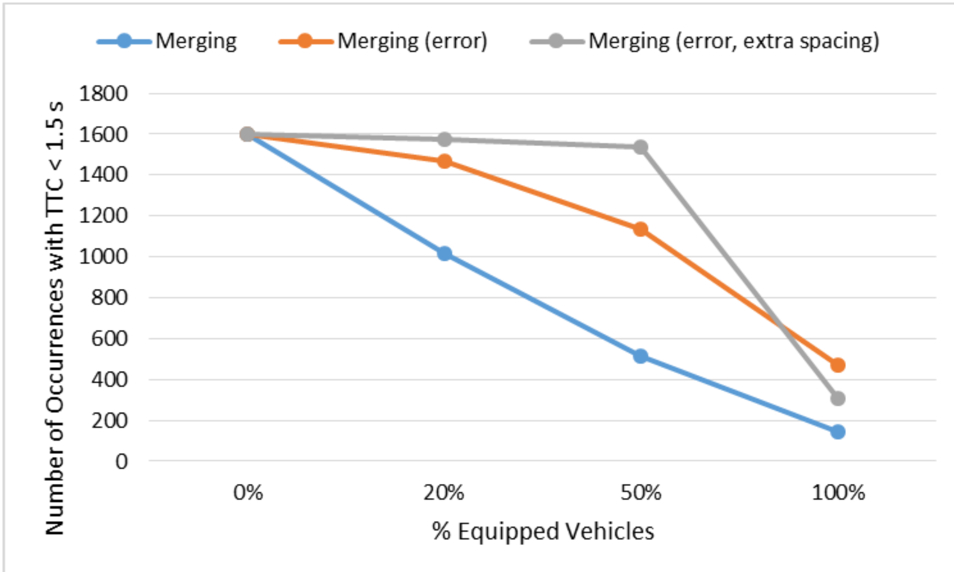

Figure 5.11: Safety results for the 2-lane highway

The environmental impact of the merging strategies is shown in Figure 5.12. It can be seen that the energy use decreases by up to 22% when 100% of vehicles are equipped; at the lower penetration rates, the direct effect on energy use is an increase (of usually 5% or less). However, when taking into account the reduction in accident risk, the direct increase in energy use could be negated by the energy savings resulting from the prevention of an incident and the ensuing congestion.

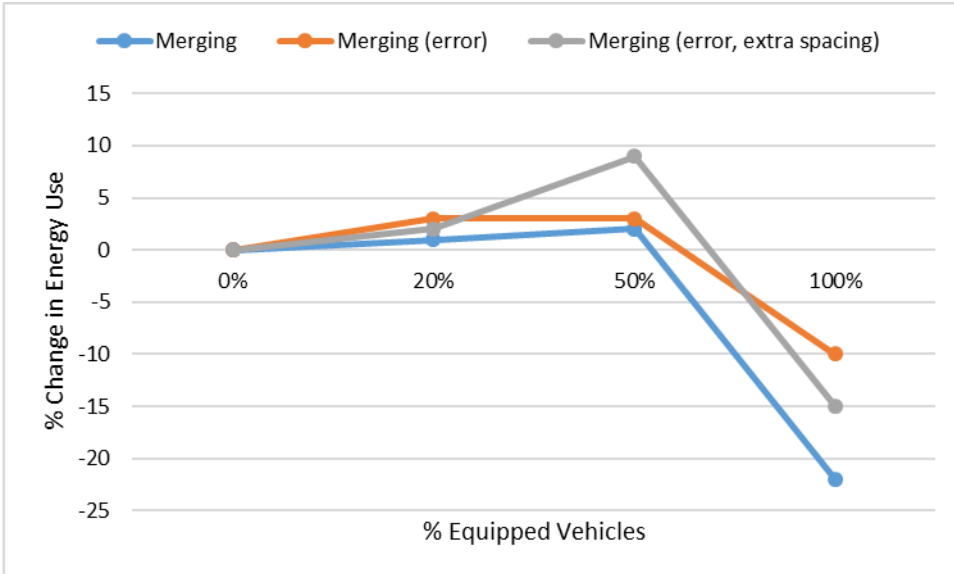

Figure 5.12: Environmental results for the 2-lane highway

5.4.2 Three-Lane Highway

Figure 5.13 shows the level of service on the three-lane highway, when none of the vehicles are using any cooperative merging strategy. Similar to the two-lane scenario, it can be seen that the Level of Service usually starts around D-E and then rises to F, generally by the 25-minute mark. When 100% of vehicles are equipped with the merging application and perfect positioning, the LOS is almost always maintained at D-E, as can be seen in Figure 5.14. In this sense, the performance of the merging algorithm is even better on the three-lane highway than the two-lane highway.

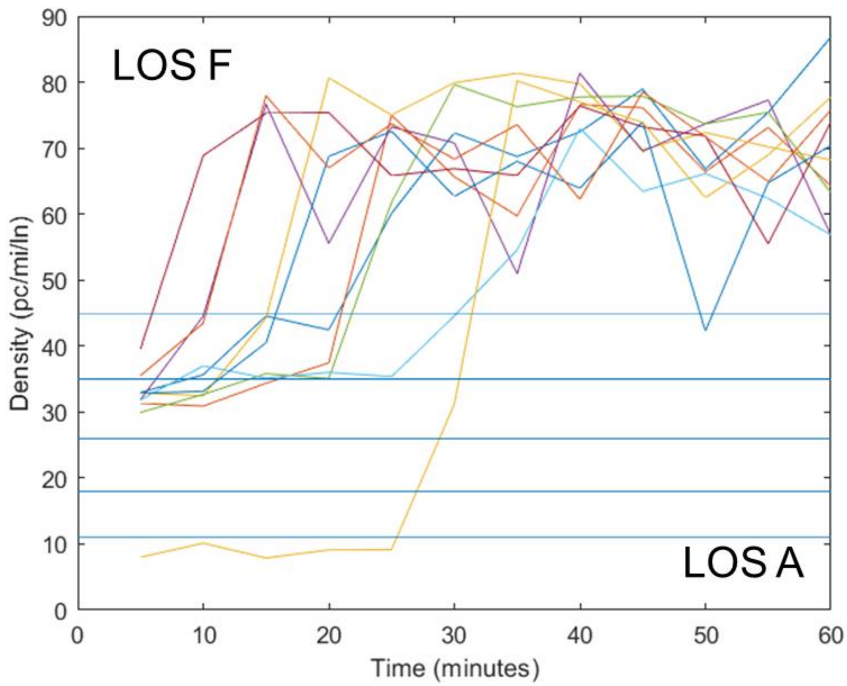

Figure 5.13: Level of Service on the 3-lane highway (0% equipped)

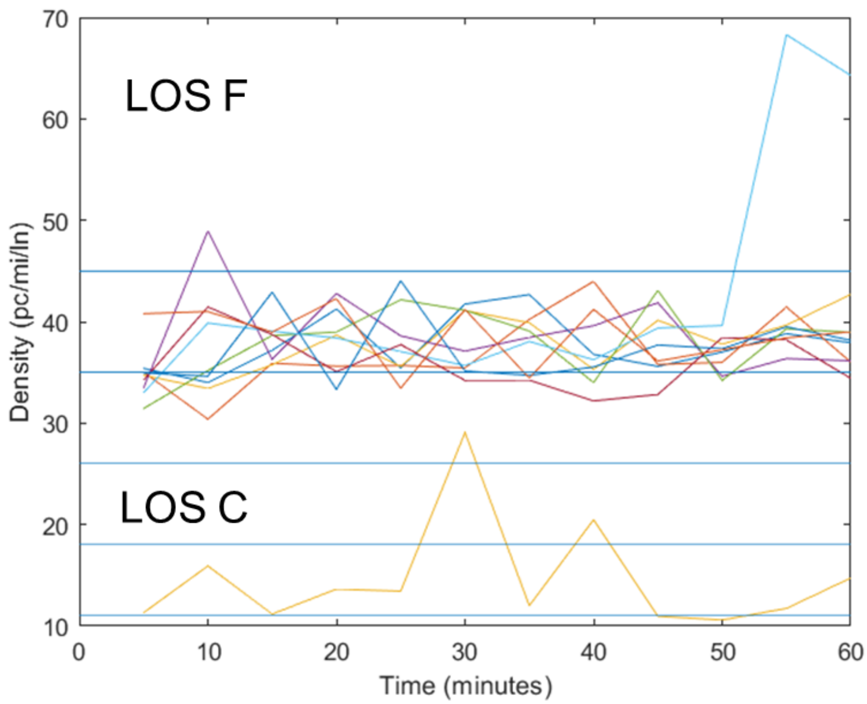

Figure 5.14: Level of Service on the 3-lane highway (100% equipped)

The difference in LOS (congestion levels) can also be seen in the network mobility metrics (see Figure 5.15), which shows that equipping 100% of vehicles with the merge application increases average speed on the network by about 120% (from 27 mph to 58 mph). This is an even greater increase than for the 2-lane case. As expected, the mobility benefit increases with the percentage of equipped vehicles—for all three merging strategies, on this network. When typical urban canyon position error is present, the benefits can be maintained (at least at 20% and 50% penetration rates) by increasing the spacing. In fact, this strategy even appears to outperform the merging strategy with perfect positioning at those penetration rates.

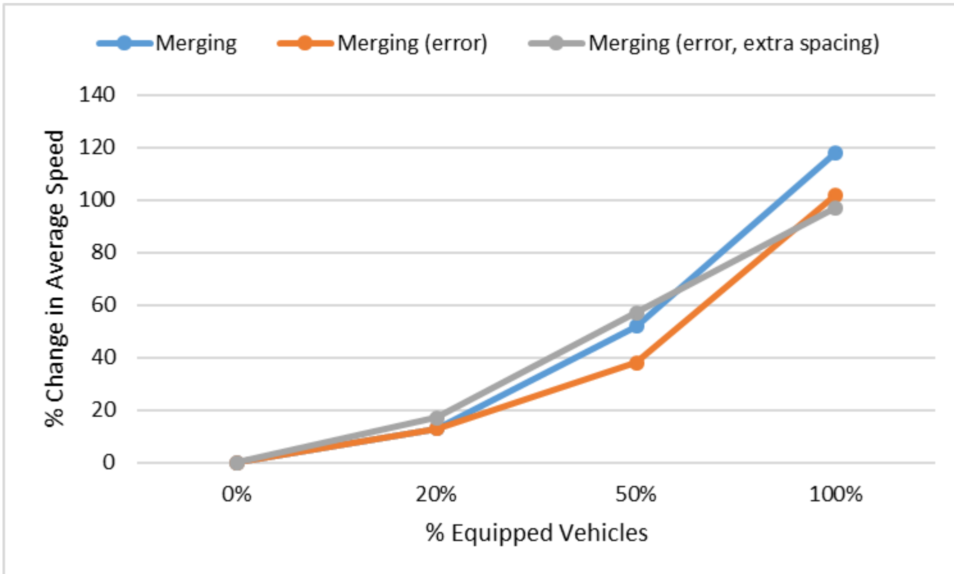

Figure 5.15: Mobility results for the 3-lane highway

Figure 5.16 shows the effect on network-wide safety, in terms of the number of potential conflicts. As with the Mobility results, the benefits of all three merging strategies increases with an increasing percentage of equipped vehicles, and the "with error" algorithm performs better with the increased spacing. But unlike the Mobility results, the merging strategy with perfect positioning performs best. Notably, it has a large benefit at low penetration rate: it reduces the number of conflicts by 40% when only 20% of vehicles are equipped.

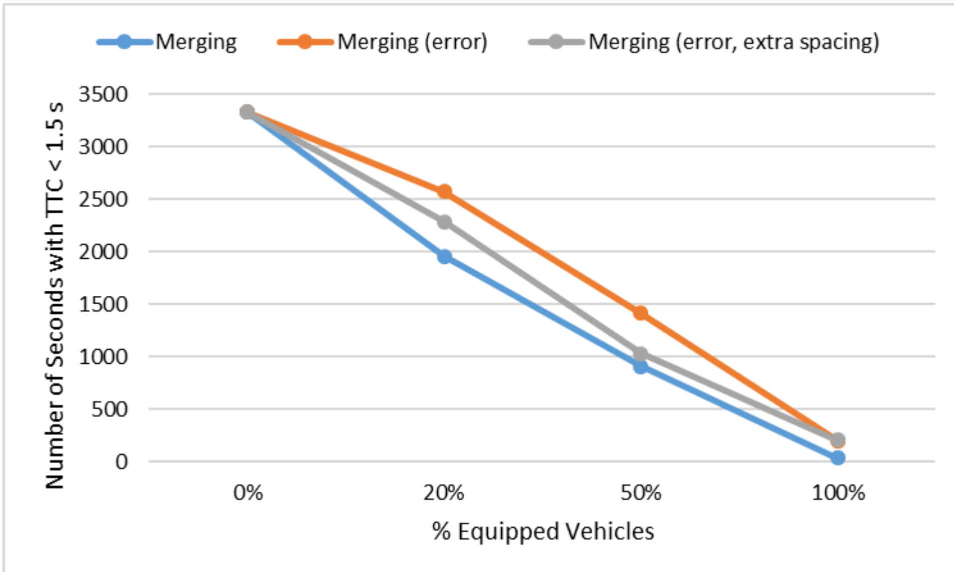

Figure 5.16: Safety results for the 3-lane highway

Similar to the safety and mobility results, the energy use shows benefits for every merging strategy and penetration rate tested (see Figure 5.17). Similar to the trends for safety and mobility, the energy savings increase with increasing penetration rate, up to a maximum of 31% energy savings.

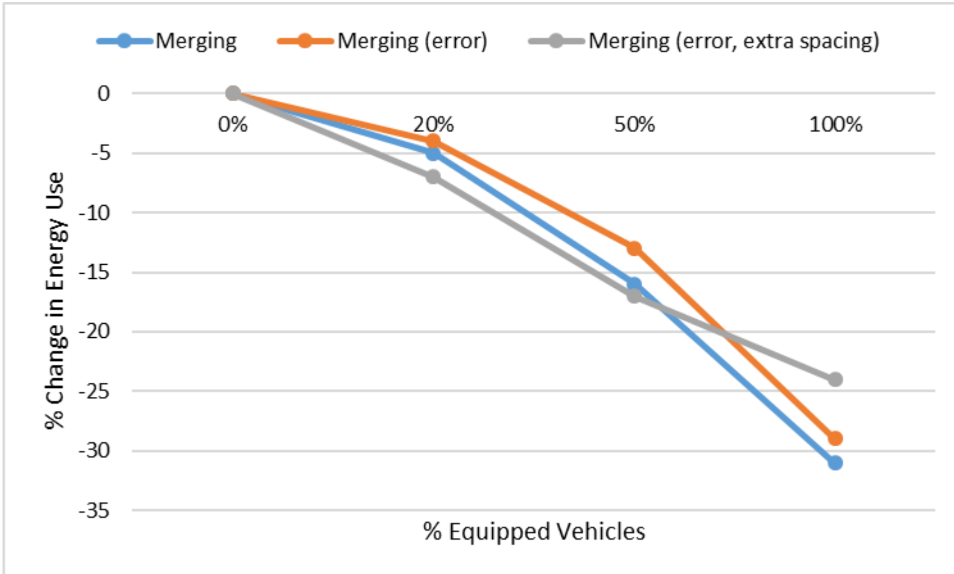

Figure 5.17: Environmental results for the 3-lane highway

5.5 Summary and Discussion

This chapter describes the development and testing of three cooperative merging strategies. This set of strategies is novel in two ways. First, all three can handle varying percentages of application-equipped vehicles (anywhere between 0% and 100%), sometimes showing significant benefits at penetration rates as low as 20%. To the authors' best knowledge, no other cooperative merging strategy to date has shown significant benefits at such a low penetration rate. Second, two of the cooperative merging strategies presented are able to accommodate position errors representative of a state-of-the-art GNSS positioning system traversing an urban canyon.

The final application could incorporate all three merging strategies, for example by simply choosing the best one based on circumstances (i.e., when in an urban canyon, use one of the strategies that can handle error, whichever is better; and when in an open-sky area, use whichever of the three strategies performs best in that scenario). Of course, further testing is needed to capture the huge diversity of scenarios in the real world, and it is very likely that the merging strategies could be refined to increase benefits in these various scenarios.

6 Anticipatory Lane Change Application

6.1 Overview

Another highway application called Anticipatory Lane Change Warning (ALC) was developed in this dissertation. Like the cooperative merging application, it improves safety of the overall traffic stream by reducing the number of potential crashes. However, it relies more on ranging sensors for positioning, and thus is less affected by GNSS position error. Even so, GNSS position error may have negative consequences for the application, as discussed in Section 6.6.

Anticipatory driving, or adjusting one's driving behavior in anticipation of the future movements of surrounding vehicles, plays an important role in reducing the number of road accidents [Stahl *et al.*, 2013]. It is generally associated with experienced drivers, though could possibly be coded into the behavior of automated vehicles. The role of anticipation in driving has been studied in the literature [Stahl *et al.*, 2013; Treiber *et al.*, 2007]. In [Treiber *et al.*, 2007], the authors incorporate anticipation of the movements of vehicles ahead into a car-following model (e.g., braking in reaction to several vehicles ahead) and show that this increases the stability of traffic flow. In a lane change scenario, the future situation of the *target* lane is equally important.

Conventional lane change warning and automated lane changing systems detect other vehicles using on-board sensors such as camera, radar, and ultrasonic sensors. One limitation of existing lane change algorithms (listed in Section 2) is that they tend to consider the traffic situation only in terms of the lane-changing, or "host", vehicle (HV in

Figure 6.1), the preceding vehicle (Vehicle C), and the vehicles in front of and behind the intended gap in the target lane (Vehicles B and A, respectively). However, a normal lane change takes at least a few seconds to complete, during which time the situation may change significantly. Critically, the gap may become too small to be safe: for example, if Vehicle D brakes just as HV starts to change lanes, Vehicle B may brake as well. As a result, the gap between Vehicles A and B may become unsafely small by the time HV completes the lane change. While this can be avoided to some extent by aborting the lane change maneuver midway [Luo *et al*., 2016], a better option (both in terms of safety and traffic flow) is not to initiate the maneuver in the first place.

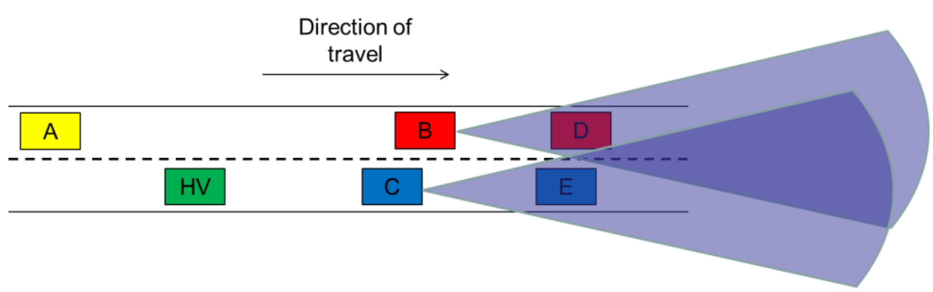

Figure 6.1: Example pre-lane change situation

To enable this option, it is first necessary for HV to detect Vehicle D. In literature on automated lane changes, vehicle detection is generally accomplished by ranging sensors (e.g., radar [Nilsson *et al*., 2016]) or wireless vehicle-to-vehicle (V2V) communication (e.g., [Luo *et al*., 2016]). An example of the latter is Dedicated Short Range Communications (DSRC) [Harding *et al*., 2014]. While HV's ranging sensors may not detect Vehicles D and E in Figure 6.1 due to the lack of line-of-sight, V2V communication does not have this line-of-sight limitation and thus can detect vehicles occluded by others (i.e., Vehicles D and E).

The application presented in this chapter utilizes motion information about vehicles further ahead (obtained via V2V communication) to "anticipate" the movements of the surrounding vehicles, enabling better decision-making with regard to lane changing. In particular, this information is used to prevent a lane change if it is predicted that such a lane change would place the vehicle in an unsafe situation. This work has been presented in [Williams *et al*., 2018b]. The rest of this chapter is organized in the following way. Section 6.2 describes the ALC algorithm. Section 6.3 describes assumptions regarding vehicle detection, and Section 6.4 details how motion prediction is carried out. Tests of the algorithm using traffic simulation are described in Section 6.5, and Section 6.6 remarks on how the application would be affected by position uncertainty. A summary and discussion are provided in the final section.

6.2 Algorithm

The starting condition for the algorithm is that the application-equipped vehicle wishes to change lanes (see Figure 6.2). The outcome is that the lane change is either delayed or not. When considering manually-driven vehicles, this assumes that the driver heeds the lane change warning. The first check in the algorithm is whether the lane change is discretionary (e.g., changing to a faster lane). This is because the algorithm only delays mandatory lane changes, such as those required to exit the freeway. The next steps in the algorithm check whether Vehicles A-E are detectable by HV, because this is required for HV to predict the motion of all 6 vehicles over the next 3 seconds. If it is predicted that there will be sufficient (in terms of safety) headway in front of and behind HV at the end of the prediction time window, then the lane change is allowed to proceed. Otherwise, it is delayed.

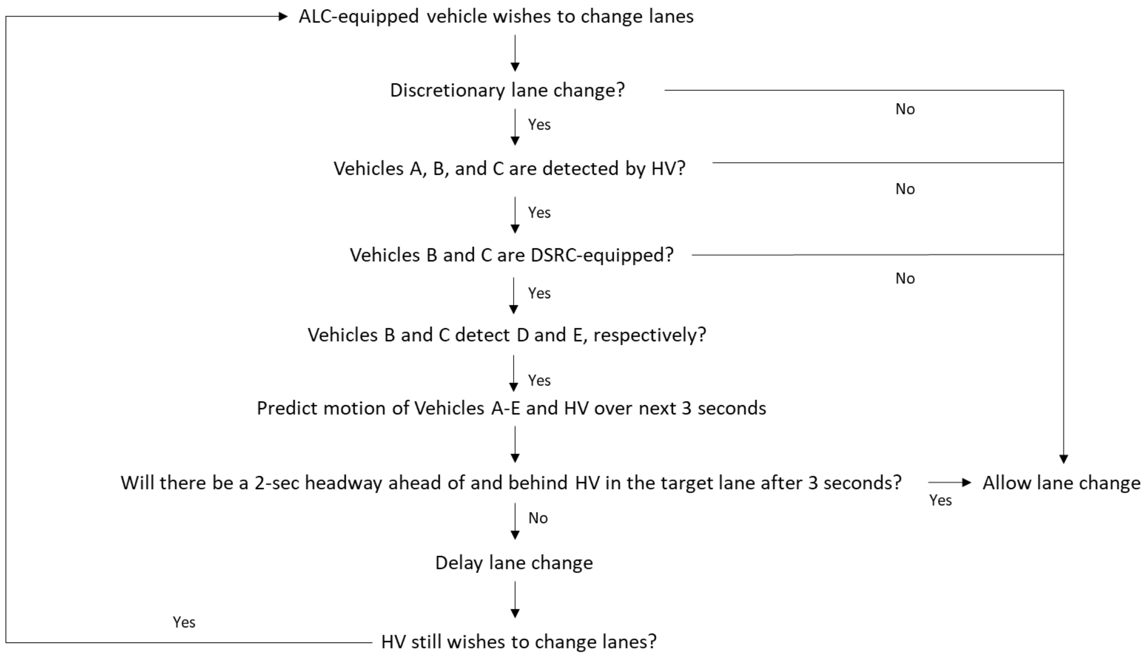

Figure 6.2: ALC algorithm flowchart

6.3 Vehicle Detection

For this algorithm to work, the motions of Vehicles A-E and the HV must be predicted and therefore, these vehicles must all be detected by HV. We assume that the HV is equipped with ranging sensors, such as radar, that can detect Vehicles A-C if they are within the range and field of view of the sensors. In our study, we consider the HV to be equipped with four corner radars and one front radar. Each corner radar, based on the

Bosch Mid-Range Radar (MRR) rear[1], is modeled as having a range of 80 m and field of view of 90 degrees. The front radar, based on the Bosch MRR front radar[2], is modeled as having a range of 160 m and field of view of 20 degrees. The location of the radars on the HV, along with their field of view and range relative to one another, are depicted in Figure 6.3. For Vehicles A and B to be detected, they must be within the range of the nearest corner radar. For Vehicle C to be detected, it must lie within range of the front radar. Vehicles B and C must be equipped with sensors for detecting Vehicles D and E, respectively; for this purpose, it is assumed that they are equipped with the same front radar as HV. Vehicles B and C must also be DSRC-equipped, in order to transmit D and E's information back to HV.

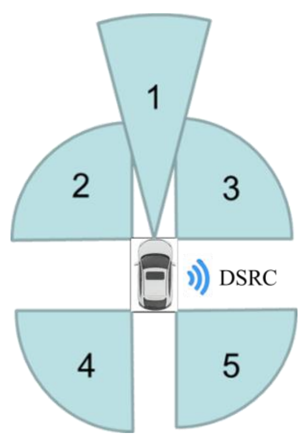

Figure 6.3: Locations of radar on ALC-equipped vehicle

[1] https://www.bosch-mobility-solutions.com/en/products-and-services/passenger-cars-and-light-commercial-vehicles/driver-assistance-systems/lane-change-assist/mid-range-radar-sensor-mrrrear/

[2] https://www.bosch-mobility-solutions.com/en/products-and-services/passenger-cars-and-light-commercial-vehicles/driver-assistance-systems/predictive-emergency-braking-system/mid-range-radar-sensor-(mrr)/

6.4 Motion Prediction

If the vehicles corresponding to Vehicles A-E in Figure 6.1 are all detected by HV as described above, it is assumed that their current positions, speeds, and accelerations are known. This is because radar measures the positions and speeds of detected objects relative to the ego-vehicle. Acceleration can be estimated from current and previous speed measurements, if the measurement update rate is sufficiently high (for radar, the rate is generally 10 Hz or higher).

To predict the positions and speeds of all 6 vehicles at the end of the three-second time window, kinematics and an empirical car-following model are used. The main premise of the car-following model is that: if one vehicle is following another closely enough, its acceleration/deceleration can be predicted as a function of its speed, the speed of the vehicle ahead, and the distance between the two. The predicted acceleration is based on the situation one second earlier, to account for human reaction time. This is similar to the Gazis-Herman-Rothery, or "general", car-following model [Brackstone and McDonald, 1998]. Our model was constructed using second-by-second vehicle trajectory data from a VISSIM freeway network, which included a mix of traffic conditions ranging from congested to free flow.

The car-following model was constructed as follows. For each observed deceleration, the positions and speeds of the decelerating vehicle and its preceding vehicle one second earlier were recorded. Then, the observed decelerations were binned based on speed of the ego vehicle and relative speed of the preceding vehicle. For each combination of speed bin and relative speed bin, deceleration was plotted as a function of the two vehicles' spacing (front bumper-to-front bumper distance). Figure 6.4 illustrates an example, showing speed bin 15-25 mph and relative speed bin -20 to -10 mph.

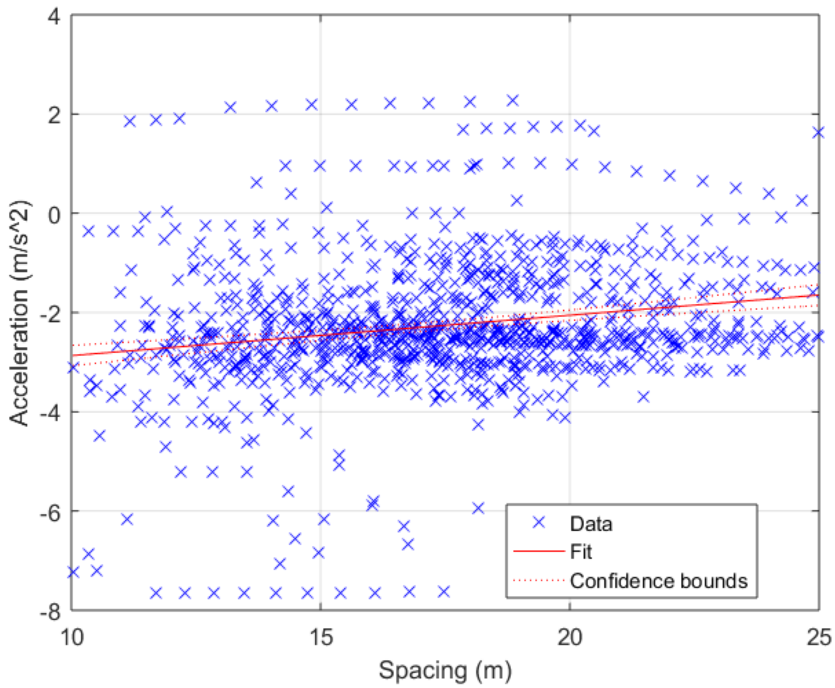

Figure 6.4: Example spacing vs. acceleration plot

Figure 6.4 shows that within the range of spacing shown (10 to 25 m), the average deceleration is about -3 m/s^2. Extending this method to other speed bins and relative speed bins, a lookup table for "next-second" deceleration was generated. If any input parameter for the lookup table falls outside the prediction regime (e.g., spacing > 25 m for the example shown), no prediction is made and the algorithm does not delay the lane change.

If the input parameters to the car-following model fall within the prediction regime and a deceleration is predicted, kinematics are then used to derive the vehicle's speed and position. Speed is obtained using equation (6.1) and then position is obtained using equation (6.2), where x_t, v_t, and a_t represent position, speed, and acceleration at time *t*. The subscript *t-1* denotes the data of the previous time step.

$$v_t = v_{t-1} + 0.5(a_t + a_{t-1}) \tag{6.1}$$

$$x_t = x_{t-1} + 0.5(v_t + v_{t-1}) \tag{6.2}$$

If the positions and speeds of all 6 vehicles at t=3 seconds are successfully predicted in this manner (t=0 represents the start of lane change intention), the next step in the algorithm is to check whether the gap between Vehicles A and B will be safe at the end of the lane change maneuver. Generally, the recommended headway for safety is 2-3 seconds at a minimum [Ayres *et al.*, 2001; California Department of Motor Vehicles, 2018]. Therefore, the algorithm prevents a lane change if the predicted headway in front of or behind the HV at the end of the three-second lane change window will be less than 2 s. This assumes that the HV's position along the road will be the same as if it had not changed lanes; only its lateral position (lane) will be different.

6.5 Simulation Setup and Results

The microscopic traffic simulator VISSIM version 9 [PTV Group, 2018] was used to evaluate the impact of this algorithm on network-wide safety and mobility under a variety of traffic scenarios (different congestion levels and penetration rates of the application). The chosen safety metric was number of conflicts, as estimated by the SSAM model. Average speed, taken as the average of all vehicles' speeds at all time steps, was used as the measure of mobility.

Ten simulation runs were conducted for each different configuration (configuration being a unique combination of several simulation settings: the network, traffic volume, and DSRC/ALC penetration rate). Each set of ten runs utilized the same 10 “random seed” numbers, for a fair comparison.

6.5.1 Hypothetical Network

To test the effect of ALC, a simplified, hypothetical freeway segment was initially used. The segment is one mile long, straight, and has 3 lanes (all in the same direction). The length of each simulation one hour (in simulation time). The impact of the application was tested at different traffic volumes and penetration rates. Two levels of traffic flow were tested: 5,000 vph (vehicles/hour) and 7,000 vph, which represent medium and heavy traffic, respectively. At 5,000 vph, ALC had negligible impact on mobility (average speed increased by 0.1%) and small impact on safety (average number of potential conflicts per simulation run dropped from 10 to 9), even when all vehicles were ALC-equipped. The low impact of ALC at this level of traffic volume is probably due to the low vehicle density: ALC is not activated very often.

At 7,000 vph, ALC has a much larger impact on safety. The average number of potential conflicts without ALC is 31, and ALC decreases the number of conflicts by a median of 28%. This can be seen on the “100% Penetration Rate” box plot in Figure 6.5. Figure 6.5 also shows the effect when the percentage of ALC-equipped vehicles in the traffic stream (“penetration rate”) is less than 100%. When the penetration rate is lower, the safety benefits decrease, which is expected. At all penetration rates, the effect on mobility is small: the median change in average speed is between 0 and +1%. The small effect on mobility could be due to the following reasons, which cancel each other's mobility effects: 1) ALC may delay a vehicle which is attempting to move to a faster lane, thus lowering its trip average speed; and 2) ALC lowers the amount of weaving, increasing the average speed because vehicles do not have to brake for other vehicles cutting in front. Weaving also results in short headways between vehicles, which are potentially dangerous.

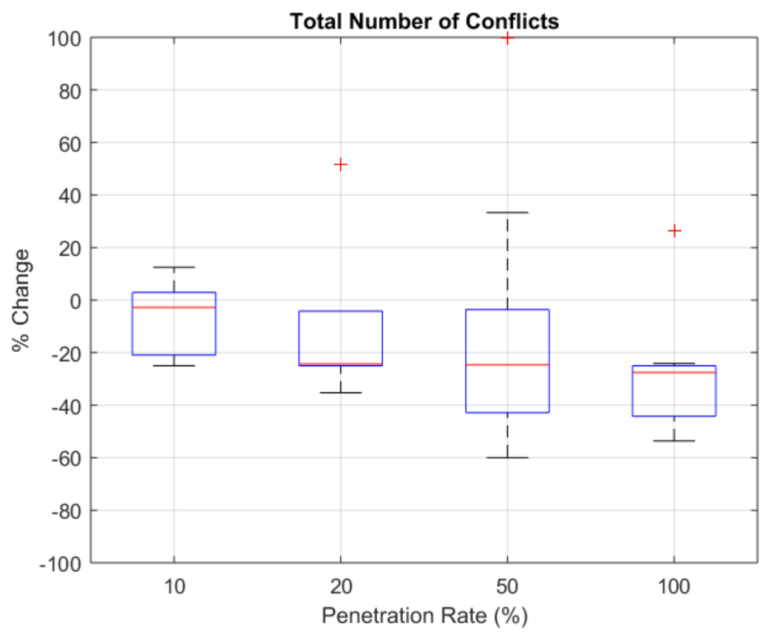

Figure 6.5: ALC results on hypothetical network (7000 vph)

Overall, these results suggest that the application can enhance freeway safety with no cost to mobility, at least at application penetration rates of 20% or higher (the median decrease in number of potential conflicts is 20% or more at these levels).

6.5.2 Real-world Freeway Network

Next, the effectiveness of ALC was tested on a real-world freeway network. The network is based on a 17 mile-long segment of the northbound Interstate 270 (“I-270”) in Columbus, Ohio. It has multiple curved sections and 9 pairs of on- and off-ramps (see Figure 6.6). The number of lanes along the mainline is usually 3-5, and the network flows were calibrated using real-world weekday peak hour traffic data. Each simulation run was two hours long (simulated hours).

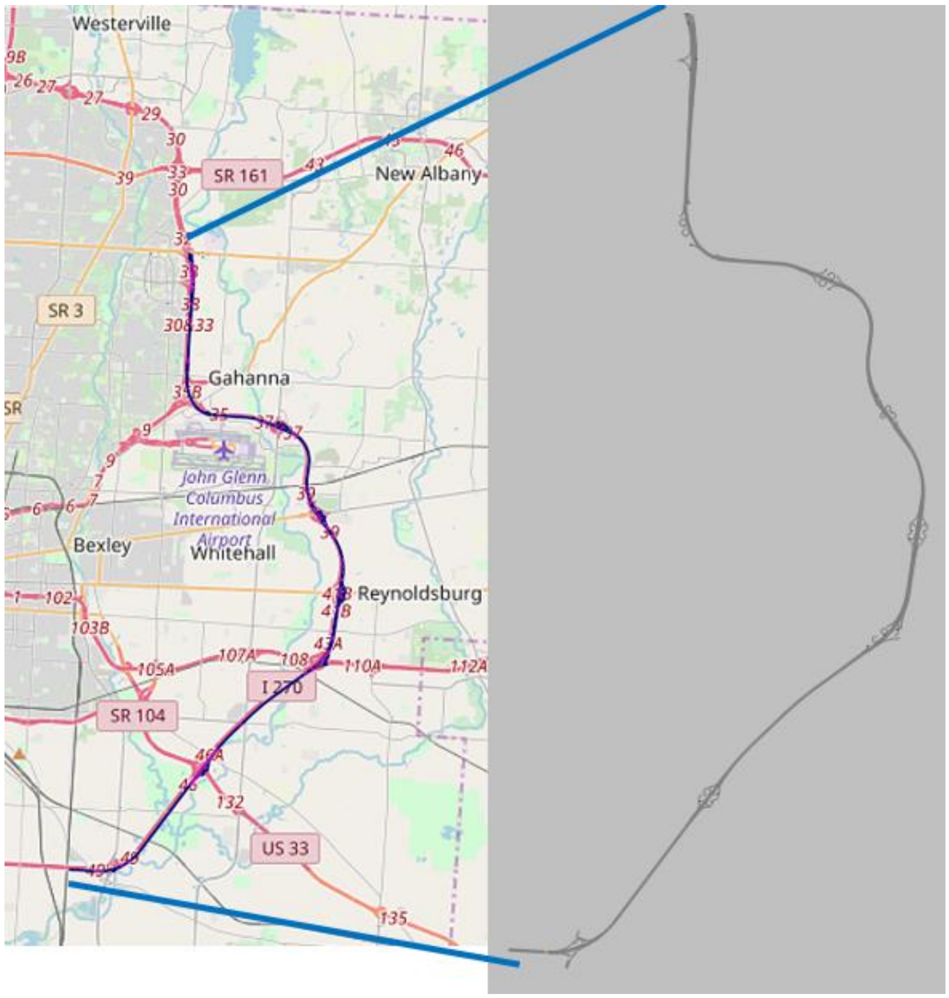

Figure 6.6: Real-world network used to test ALC (I-270 in Columbus, OH)

Without ALC, the average number of potential conflicts per simulation run is approximately 600. When 100% of the vehicles are ALC-equipped, this number drops by about 30% (see Figure 6.7), similar to the “heavy traffic” (7,000 vph) results for the hypothetical network. This benefit decreases at lower penetration rates of ALC, as shown in Figure 6.7. For example, at a 10% penetration of ALC, the median reduction in conflicts drops to 15%.

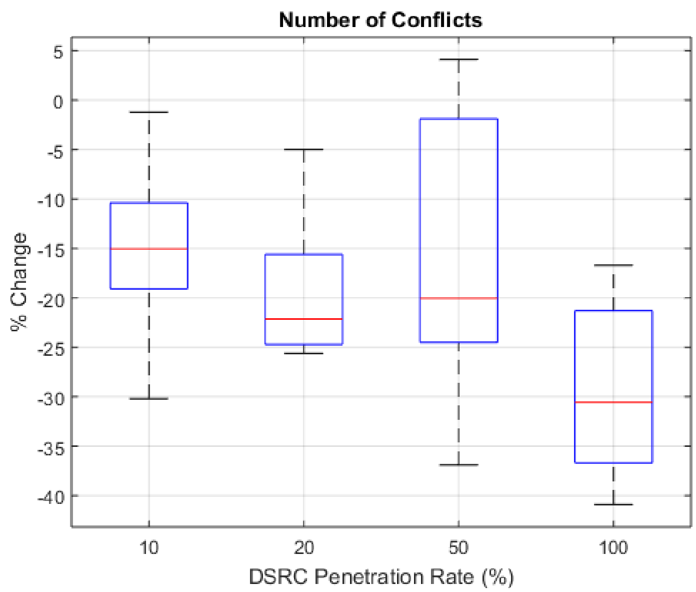

Figure 6.7: ALC results on real-world network (100% penetration of ALC)

If the ALC penetration rate is only 9% of the DSRC-equipped vehicles (to represent the market share of a major automaker that chooses to equip its vehicles with ALC), the reduction in number of conflicts is generally lower (see Figure 6.8). Interestingly, the median reduction in number of conflicts tends to stay fairly constant at around 15% for DSRC penetration rates ranging from 10% to 100%.

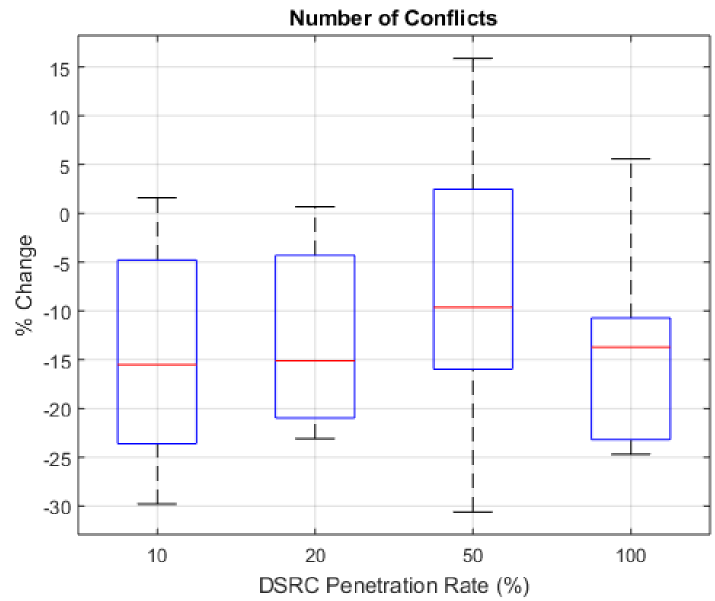

Figure 6.8: ALC results on real-world network (9% penetration of ALC)

Whether the penetration rate of ALC is 9% or 100% of DSRC-equipped vehicles, ALC's effect on mobility is small: it changes the average speed on the network by 1% or less for every run. This corroborates the results obtained on the hypothetical network. Overall, the I-270 results suggest that when the DSRC penetration rate is 10%, only 9% of those vehicles need to be ALC-equipped (i.e., if equipping 100% of DSRC-equipped vehicles with ALC does not appear to provide benefits). However, at higher DSRC penetration rates, the safety benefits can be increased by loading ALC on 100% of the DSRC-equipped vehicles.

6.6 Effect of Position Uncertainty

In the ALC application, position uncertainty may affect the object matching performance when matching objects detected by different sources of positioning information. For example, in Figure 6.9, for HV to obtain Vehicle D's position and speed, it must first match its ranging sensor measurement of B with Vehicle B's GNSS position (communicated wirelessly, together with B's distance measurement of D). The reason B must be detected by HV's ranging sensor is so that it can be correctly identified. Otherwise, there may in fact be another vehicle just upstream of "B", making this other vehicle the true B. If the GNSS position of HV, B, or C is incorrect, the object matching may be incorrect. For example, if B's GNSS position measurement is the grayed-out Vehicle B in Figure 6.9, HV may not be able to match it with the ranging sensor-detected B. This object-matching problem has been the subject of several studies [Chen *et al*., 2015; de Ponte Müller *et al*., 2016]. The following would increase the likelihood of correct object matching:

1. Using vehicle tracks (position histories), rather than instantaneous positions only, for matching [Chen *et al*., 2015].
2. Not too many Connected Vehicles near B, or at least their position error does not cause their measured positions to overlap with B's measured or true position.

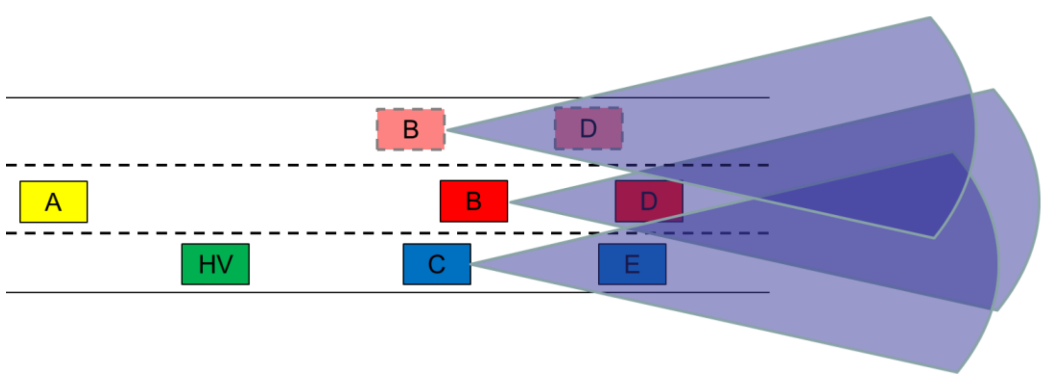

Figure 6.9: Example pre-lane change situation, with position error

6.7 Summary and Discussion

Conventional lane change warning and automated lane changing systems detect other vehicles using on-board sensors such as camera, radar, and ultrasonic sensors. With the advent of Connected Vehicle (CV) technology, wireless communication (e.g., Dedicated Short Range Communications, or DSRC) becomes another option for "sensing" surrounding vehicles. In particular, DSRC does not have the line-of-sight limitation of ranging sensors and thus can "see" traffic farther ahead, which lends itself well to anticipating the movements of nearby vehicles. This chapter presented an algorithm that uses such data to predict whether a desired lane change will result in an unsafe situation, and prevents the lane change if that is the case. The effectiveness was evaluated in the microscopic traffic simulator VISSIM using a freeway network that has been well calibrated with rush hour traffic data. System performance in terms of safety was estimated using the Surrogate Safety Assessment Model (SSAM) under a variety of traffic scenarios (different congestion levels, penetration rates of connected vehicles and application-equipped vehicles). Tests showed that the proposed algorithm could reduce the number of potential traffic conflicts by up to 30% without impacting mobility, with higher reductions at higher traffic volumes and higher percentages of application-equipped vehicles.

7 Conclusions and Future Work

The overarching goal of the work in this dissertation is to help bring the safety, mobility, and environmental benefits of Connected Vehicle (CV) technology to the public sooner, by developing new CV applications, highlighting the gap between affordable positioning and application requirements, and finding ways to close the gap (for example, by integrating position uncertainty into the applications). The specific areas which have been addressed in this dissertation are: 1) the positioning requirements of CV applications, 2) the impact of position uncertainty on CV applications, 3) modelling of realistic GNSS position error in simulation, 4) development of a novel cooperative merging application which is able to tolerate such position error, and 5) development of a novel highway application for improving the safety associated with lane changes.

Section 7.1 provides the conclusions and Section 7.2 provides some of the future directions for the research.

7.1 Conclusions

Chapter 3 describes a qualitative analysis of the positioning requirements of a wide variety of CV applications. The requirements examined were the required level of accuracy, type of positioning, and positioning update rate. It was found that coarse (lower accuracy than lane-level) positioning enables 82% of applications. Lane-level accuracy enables the remaining applications, which are mostly safety applications. 80% of applications either require or benefit significantly from lane-level accuracy.

Chapter 4 went further to *quantify* the impact of position uncertainty on two CV applications, Eco Approach and Departure at Signalized Intersections (EAD) and High Speed Differential Warning (HSDW). It was found that using positioning of insufficient accuracy could cause application benefits to drop significantly, for both applications.

Chapter 5 describes the development and testing of a cooperative merging application which is able to tolerate the GNSS position errors typical of an urban canyon. It was found that adjusting the application, by increasing inter-vehicle spacing, could increase application performance in some scenarios. Notably, this cooperative merging application shows significant safety, mobility, and environmental benefits, even at low (20%) penetration rate. This is important, because it shows the potential for merging as one of the "early deployment" applications.

In Chapter 6, another developed application, Anticipatory Lane Change Warning (ALC), is presented. This application predicts whether an intended lane change will result in an unsafe situation, and prevents it if that is the case. Simulation tests on two highway networks, including a very large one calibrated using real-world data, suggest that the application increases safety (up to 30% reduction in conflicts) without slowing down traffic. As expected, the benefits increase with increasing penetration rate of the application.

7.2 Future Directions

While this dissertation contains its fair share of research findings and contributions to the field, there is plenty of work still left to be done in this area. This is described below, where each subsection corresponds to a chapter in the dissertation.

7.2.1 Impact of Position Uncertainty on EAD and HSDW

Regarding the HSDW application, it would be interesting to test the application's sensitivity to longitudinal position error, not just lateral error. This way, the need for improved positioning in the longitudinal direction can be assessed (it is clear that lane-level accuracy in the lateral direction is required). It can also serve as the first step in making the application more robust to longitudinal position error. Also, it should be tested with the urban canyon error model developed in Section 5.2, and a position error-tolerant (PE-T) version of HSDW can be developed in tandem.

7.2.2 Position Error-Tolerant Cooperative Merging Application

There is a plethora of future research directions, in both the areas of algorithm development and testing. There are multiple ways in which the cooperative merging algorithm could be improved. First, the algorithm should be generalized so that it can be used in a wider variety of scenarios (for example, when the on-ramp is too short for vehicles to accelerate to free-flow speed). In this case, the sequence in which vehicles merge should not be determined by distance to merge point, but rather by a different metric like time-to-arrival. Second, the benefits could potentially be increased by refining the merging algorithm so that vehicles pre-emptively slow down before reaching the merge zone (if congestion and lower speeds are present on the highway). This should facilitate smoother merging, leading to increased benefits for all three of the merge algorithms tested.

Regarding the testing of the merge algorithm, it was shown that increasing the spacing between vehicles could improve overall system performance. Therefore, a sensitivity analysis should be conducted with respect to spacing to determine the optimal value. The algorithm should also be tested at a 10% penetration rate. Since there were already substantial benefits at 20% penetration rate (in some cases), if it also shows benefits at 10% penetration this could serve as a major incentive for automakers to adopt it as an "early deployment" application.

Finally, the position error model could be refined by incorporating other sensors (for example, if the vehicle has just entered an urban environment, its position accuracy can be temporarily maintained through dead reckoning). Also, the correlation of GNSS errors should be taken into account. That is, differencing nearby GNSS positions eliminates the common mode errors without need for differential corrections.

7.2.3 Anticipatory Lane Change

Future work could examine the effect of position error on the application. As mentioned in Section 6.6, GNSS position error could potentially interfere with matching between V2V- and radar-detected objects. Also, the impact of this application on energy use and emissions should be investigated in addition to the already-measured safety and mobility.

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