IMPACTS OF VEHICLE AUTOMATION ON TRAFFIC FLOW STABILITY

BY

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DISSERTATION

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ABSTRACT

This dissertation is motivated by the possibility of a small number of autonomous vehicles (AVs) or partially autonomous vehicles that may soon be present on our roadways. This automation may take the form of fully autonomous vehicles without human intervention (Society of Automotive Engineers, SAE Level 5) or, as is already the case in many modern vehicles, may take the form of driver assist features such as adaptive cruise control (ACC), or other SAE Level 1 features. Regardless of the extent of automation, changing the vehicle dynamics of a small number of vehicles in the bulk traffic flow may have substantial implications on the underlying traffic flow and may influence the development of emergent phenomena such as phantom traffic jams, or traffic stability.

This dissertation has four main contributions: (i) experimental evidence to validate that human driving behavior alone is sufficient for the development of phantom jams, (ii) theoretical work as well as experimental work to demonstrate that current commercially-available ACC systems may be string unstable under certain circumstances, (iii) theoretical and experimental results that demonstrate the ability of autonomous vehicles to stabilize traffic flow and prevent phantom jams from arising even at low autonomous vehicle penetration rates (∼5%), and (iv) experimental evidence for the emissions impacts of phantom traffic jams, and the potential for AVs to substantially reduce these emissions.
To my grandparents,
Melba, Jerome, Ingeborg, and Erwin
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Chapter 1

Introduction

1.1 Motivation

This dissertation is motivated by the rapid gains being made by autonomous vehicles (AVs) and the reality that there may soon be a small number of AVs on our roadways. Even sooner, driver assist features such as adaptive cruise control (ACC) are the first step toward an autonomous future and may substantially alter traffic flow on highways. While ACC vehicles have long been considered a premium feature on luxury vehicles, this is no longer true. Several large car manufacturers have introduced ACC as a standard feature on most, if not all models, and through the second quarter of 2018, 16 of the 20 best selling cars in the US were available with ACC.

As was shown by the seminal work of Sugiyama, et al. [1], human-piloted traffic may be be unstable causing traffic waves and phantom traffic jams to appear on roads even in the absence of bottlenecks. These phenomena increase fuel consumption and cause potentially dangerous situations and decrease throughput.

While features such as ACC may improve rider comfort, and AVs promise a safer transportation future, it is still unclear what their impacts are on traffic flow and stability when a small fraction of vehicles drive with substantially different dynamics than the remaining vehicles. Therefore, this dissertation addresses both
the potential impacts on traffic stability of driver assist features such as ACC, as well as the extent to which AVs could be used to positively influence traffic flow and eliminate traffic instabilities. The impacts of such changes to the traffic flow have broad implications on quantities such as fuel consumption and emissions.

1.2 Related work

This section will put the work presented in this dissertation in a broader societal context in relation to other significant research efforts that have tried to quantify the impacts of AVs. While each chapter will present the relevant related work and historical context, this section aims to provide background on the prevalent thought on the impact that AVs may have on a wide variety of aspects of society.

Interest in AVs has increased significantly over the past several years. This is partially because transportation engineering is currently at a crucial point: new, transformative technologies such as vehicle automation and connectivity as well as ubiquitous sensing have the potential to alter the way we think about urban mobility [2]. This promises to change transportation engineering much like the creation of the Interstate Highway System did in the 1950s, a climate in which many of the seminal transportation research initiatives were started. However, much like during the 1950s and 1960s, it is still unclear where this new technology will lead transportation engineering. Many questions remain on how AVs, which may soon begin to enter our roadways, will influence traffic flow and estimation, as well as broader societal concepts such as travel habits, vehicle ownership, and even land use.

One prominent question is how the introduction of AVs will influence travel patterns and vehicle miles traveled (VMT). Since AVs do not require a driver, it is possible that they could be used as shared autonomous shuttles, matching riders with similar temporospatial trips to the same vehicle much like many transportation network companies such as Lyft and Uber do with their pooled rides (Uber Pool
and Lyft Line). This has the potential to significantly reduce the total number of required trips, and thus could reduce VMT. For example, recent work by Alonso-Mora, et al. [3] shows that 20% of the taxis in New York City could serve 98% of the trip demand with a mean trip delay of 3.5 minutes if pooling were conducted across all taxis. Such a system could be implemented with AVs acting as shared shuttles.

However, just as AVs have the potential to decrease VMT, there is a possibility that they will serve to increase VMT if, instead of being viewed as a shared resource, AVs are thought of as personal chauffeurs. In a preliminary experiment, Harb, et al. [4] addressed the shift in travel patterns that AVs may have. Since AVs are currently cost prohibitive for large-scale behavioral studies, Harb. et al. provided participants with a chauffeur who would drive them (or or their vehicle without passengers). Travel behavior was observed both when participants were responsible for driving themselves, and for the period when the chauffeur was made available. Overall, VMT increased by 76% during the experiment for the participants. Noticeable was that the most significant increase in VMT was for retirees, who stated that they felt more comfortable traveling longer distances or at night when it was dark. This indicates that AVs may also play a role in enabling accessible travel solutions for people from all walks of life. However, nearly 20% of trips were found to be “ghost trips,” where no passenger was in the vehicle (e.g., sending the vehicle to find parking or pick up laundry or friends) [4]. This indicates that the convenience of personal AVs may substantially increase VMT.

Another way in which AVs may change the urban fabric is by altering land use patterns. Similarly to the possible impacts of AVs on VMT, there are several possibilities for how AVs might influence land use and the growth of cities [5]. Under the model of AVs serving as shared autonomous shuttles, significantly less space must be dedicated to parking infrastructure. This frees space for other uses and enables the development of high-density urban cores. However, again, if AVs act as personal chauffeurs, longer commutes may be more tolerable, and the possibility for much lower density cities becomes viable.
There is also uncertainty in how the introduction of AVs may affect energy consumption [5]. While AVs may decrease energy consumption due to factors such as platooning, eco-driving, congestion mitigation, improved crash avoidance, and a decreased emphasis on performance, other factors such as a travel cost reduction and new potential users may increase the energy used by transportation as a result of the introduction of AVs.

While fully understanding the broader impacts that AVs will have on our society and the shape of our cities is critical to assess the benefits and risks of AVs, this dissertation focuses on one particular aspect of the impact of AVs: how AVs will influence traffic flow and stability, and what potential gains in stability may mean for fuel consumption and emissions.

1.3 Contributions of this dissertation

The main contribution of this thesis is to address the question of how vehicles with increased levels of automation will alter the traffic flow, and whether this will improve traffic stability, even when only a small AV penetration rate is present on the road. Specifically, this consists of four sub-contributions that together address this question. These contributions are outlined below:

- Design and execution of a set of experiments that show the development of stop-and-go waves as a result of human driving behavior alone, and go beyond previous experimental efforts to link phantom traffic jams and vehicle fuel consumption by providing not only vehicle trajectories but also on-board data such as fuel consumption measurements.

  - As a first step toward understanding the impacts of AVs on traffic flow, a set of experiments with up to 22 vehicles are executed to observe human driving behavior both at the level of bulk traffic flow and at the level of
the individual vehicle. This experimental setup also acts as a testbed to measure the impact of an AV on traffic flow.

– A dataset is produced that contains experimental evidence for the development of phantom traffic jams as a result of human driving behavior alone. This dataset is the first of its kind to include both vehicle trajectories and on-board vehicle data such as fuel consumption, measured directly from each vehicle’s OBD-II port.

• Measure the impact of driver assist features such as adaptive cruise control on traffic stability.

  – Little is known about the empirical stability of commercially available ACC systems when considering the overall traffic stream. This work provides a comprehensive stability analysis of seven different commercially-available ACC vehicles.

  – This includes calibration of a dynamical model for ACC systems that is capable of accurately reproducing experimentally-collected ACC vehicle trajectories.

  – Using this calibrated model, a linear stability analysis is conducted on the ACC dynamical model for each vehicle. The results of the stability analysis indicate that commercially-available ACC systems are string unstable, but small modifications can be made to stabilize the system.

• Experimental results showing that even at low penetration rates (e.g., ~5%), AVs are capable of dampening phantom traffic jams if properly controlled.

  – Traffic controllers are designed and implemented on an AV with the intent of dampening traffic waves and preventing new waves from arising.

  – A series of experiments are conducted on a ring-road track that demonstrate that a single autonomous vehicle in a stream of 21 vehicles is
capable of substantially dampening traffic waves and stabilize the traffic flow. This results in a reduction in fuel consumption of up to 39% when measured across the experiment traffic stream.

- **Demonstrate the impact of phantom jams on vehicle emissions, and the ability of autonomous vehicles to reduce these emissions.**
  
  - Based on the experimental results of an AV actively dampening traffic waves, the MOVES emissions model is used to investigate the impact that an autonomous vehicle actively dampening traffic waves may have on motor vehicle emissions.
  
  - The findings of this dissertation indicate that the dampening efforts of a single autonomous vehicle in a stream of up to 21 vehicles can reduce vehicle emissions by between 15% and 73%.

1.4 Organization

A brief history of microscopic traffic flow modeling and an overview of traffic stability is provided in Chapter 2. Specifically, in Section 2.2, a history and overview of microscopic modeling is provided. In Section 2.3, the basics of traffic string stability are introduced.

In Chapter 3, experimental efforts to observe phantom traffic jams in a controlled setting are presented. Specifically, Section 3.2 explains the experimental setup and the experimental protocol. Section 3.3 describes the data collection method used to extract trajectories from a 360-degree video footage. Collected vehicle trajectory measurements are validated in Section 3.4, and the experimental data are presented in Section 3.5. This new dataset provides new opportunities in transportation research, as concluded in Section 3.6.

Theoretical and experimental results on the stability of adaptive cruise control systems are presented in Chapter 4. In Section 4.3 we review a common constant
time-headway relative velocity type model used to describe the dynamics of ACC equipped vehicles, and define the conditions under which the model is string stable. In Section 4.4, an overview of the experimental setup, including vehicle instrumentation, and description of the testing procedure is provided. The methods used to estimate the model parameters from the data collected during the experiments are given in Section 4.5. In Section 4.6, the main results are presented indicating that under the best fit parameters, the ACC systems of seven commercially-available, current model year vehicles are string unstable.

Results from a series of experiments conducted as part of this dissertation to demonstrate the ability of AVs to dampen phantom traffic jams are presented in Chapter 5. The results of each of the three experiments are presented and compared in Section 5.4. In each experiment, stop-and-go waves arise dynamically when all vehicles are under human control. Once one vehicle is activated to be autonomous (with the control algorithms described in Section 5.3), the traffic waves are dissipated. Compared to when waves are present, the Lagrangian control results in up to 39% less fuel consumption and a throughput increase of up to 15%. Future perspectives for Lagrangian vehicular control are provided in Section 5.5.

The impact of phantom traffic jams on vehicle emissions, and the potential impact that properly-controlled AVs may have on reducing vehicle emissions is presented in Chapter 6. First, we present the design of the experiment to collect data using human drivers and an AV, and discuss strategies to dampen traffic waves using an AV as well as review methods for estimating vehicle emissions in Section 6.2. The results are presented in Section 6.3 and we conclude that a small number (∼5%) of AVs in the traffic flow may significantly reduce vehicle emissions for all vehicles on the roadway in Section 6.4.

Finally, the dissertation is concluded in Chapter 7 where the key findings and limitations of this work are summarized, and suggestions for future work are made.
Chapter 2

Traffic modeling and stability

2.1 Introduction

This section provides background on phantom traffic jams, microscopic modelling, and traffic stability. These are concepts that are central to the results presented in this dissertation. This chapter also provides some historical background on traffic modeling to put the results presented in this dissertation into context.

Traffic jams that arise in the absence of bottlenecks are often referred to as *phantom traffic jams* [6, 7]. These may be stop-and-go waves where the vehicles come to a complete stop, or simply oscillatory traffic conditions that amplify as they propagate against the flow of traffic. While there are many common triggers that lead to traffic jams, the seminal experiments of Sugiyama, et al. [1, 8] demonstrated that human driving behavior alone can be sufficient to trigger these waves. This finding was later verified by Wu, et al. [9, 10], who used a similar experimental setup and observed traffic waves emerging from human driving behavior alone, as well as Jiang, et al. [11, 12], who conducted a 51 vehicle platoon experiment and observed the emergence of phantom jams as a result of human driving behavior. These jams increase fuel consumption and emissions of the traffic flow [13, 14] and decrease the throughput of the road [13].

To avoid phantom jams, it is important for a platoon of vehicles to be *string*
stable, meaning that small perturbations from an equilibrium flow are dissipated as they propagate up stream along the platoon [15]. The question of interest is thus identifying whether the interaction between two vehicles is string stable. This can be done by analyzing the car following dynamics of the vehicles in the platoon. We first review microscopic traffic modeling and review some prevalent models in the literature. Then we review a straightforward check for stability presented in [16].

2.2 Microscopic modeling

Interest in modeling vehicle dynamics at the individual vehicle level started in the 1950s when an expanding highway system promised to improve vehicular mobility, and it became clear that data was required to understand traffic at the level of the individual vehicle. In this section we will discuss some of the prevalent traffic flow models, and how they are constructed.

The premise behind microscopic traffic flow modeling is that the trajectory of each individual can be described as a function of the vehicle’s surroundings. An example of this is a car following (CF) model where a pair of vehicles are arranged as seen in Figure 2.1. Here the acceleration of an individual vehicle is described as a function of its own state and the state of the vehicle in front of it. These take the form of

\[
\ddot{x}_j = f(\xi_j, \xi_{j-1}) \tag{2.1}
\]

where \(\ddot{x}_j\) is the acceleration of the \(j^{th}\) vehicle, \(\xi_j\) is the state vector describing the state of the \(j^{th}\) vehicle, \(\xi_{j-1}\) is the state vector describing the state of the \((j - 1)^{th}\) vehicle with vehicle order \(j = 1, 2, 3, \ldots\) as counted from the first vehicle in a platoon, and \(f\) is the function that describes the behavior of the \(j^{th}\) vehicle. More specifically, a common modeling choice is to assume that the acceleration of the following vehicle (vehicle \(j\)) is a function of the speed of the following vehicle, the distance between the lead vehicle and the following vehicle, and the relative speed
between the two vehicles. Specifically,

\[ \ddot{x}_j = f(\dot{x}_j, s, \Delta v), \] (2.2)

where \( \dot{x}_j \) is the speed of the following vehicle, \( s := x_{j-1} - x_j \) is the spacing of the two vehicles (front bumper to front bumper), and \( \Delta v := \dot{x}_{j-1} - \dot{x}_j \) is the relative speed between the two vehicles. Note that vehicles are assumed to be point particles and do not take up physical space on the roadway. The model can trivially be extended by allowing \( \ddot{x}_j = f(\dot{x}_j, g_j, \Delta v) \) where the gap between vehicles is defined as \( g_j := x_{j-1} - x_j - L \) for vehicles of length \( L \).

These microscopic models are in contrast to macroscopic models where traffic is described as a bulk flow, and conservation equations are used to describe how the flow evolves. For more on macroscopic modeling, see [17, 18].

One of the earliest CF models is that by Pipes [19], which first appeared in the 1950s. The problem studied by Pipes is that of a column of vehicles that start from rest when a stoplight turns green. While this is far from many of the microscopic car following models used today, it is important since it marks the first in a large family of such models that have dominated transportation engineering for the past half-century.

Another set of important microscopic traffic models followed experimental efforts
by researchers at General Motors in the 1950s. The goal was to collect speed and spacing data to characterize driving behavior [20, 21, 22, 23]. This work resulted in the Gazis–Herman–Rothery (GHR) model [22, 23], which stemmed from the idea that the acceleration of the following vehicle at time \( t \) should be proportional to the speed of the following vehicle, the relative speed to the lead vehicle, and the distance between the two.

The Gipps model [24] is important since it forms the basis of many microscopic traffic simulation tools. The Gipps model is based on the assumption that each driver sets limits on the desired braking and acceleration rates, which may depend on individual driver comfort or vehicle performance. The velocity of vehicle \( j \) is computed as the minimum of a two limiting velocities. However, due to the switching modes, the Gipps model may be more difficult for continuous analysis.

The above models all contain an explicit driver reaction term. In contrast, many models have been shown to reproduce realistic vehicle trajectories without explicitly accounting for driver reaction time. For example the intelligent driver model (IDM) [25] is a second-order ordinary differential equation that is capable of exhibiting phantom traffic jams that arise due to the instability of the model [16].

Another frequently used model that does not contain an explicit driver reaction time is the optimal velocity model (OVM) [26]. The OVM is based on the idea that, for a particular spacing available to each vehicle on the roadway, there is a unique (“optimal”) speed that the driver will comfortably drive at. This speed is defined by an optimal velocity function. This model will be used extensively throughout this dissertation, and is therefore described in more detail than the previous models in this chapter.

The OV model takes the form:

\[
\ddot{x}_j(t) = \alpha \left( V(x_{j-1}(t) - x_j(t)) - \dot{x}_j(t) \right),
\]

which gives the acceleration of vehicle \( j \), \( \ddot{x}_j(t) \) at time \( t \) as a function of the optimal velocity function \( V(\cdot) \), the current velocity of vehicle \( j \), \( \dot{x}_j(t) \), and a model parameter
The optimal velocity function $V(\cdot)$ takes the spacing between the lead vehicle and the following vehicle $x_{j-1} - x_j$ as the only input. While there are many reasonable choices for $V$, one common choice for the optimal velocity function that has emerged in the literature uses hyperbolic tangent:

$$V(x_{j-1}(t) - x_j(t)) = V_m \left( \frac{\tanh \left( \frac{x_{j-1}(t) - x_j(t)}{d_0} - 2 \right) + \tanh(2)}{1 + \tanh(2)} \right), \quad (2.4)$$

where $V_m$ is the maximum allowable speed and $d_0$ is a reference distance.

The OVM has frequently been used in conjunction with other models as part of a more complex and nuanced model. Many of these derivative models are able to reproduce the same type of instabilities seen in phantom jams [27, 28].

2.3 Traffic Stability

There are generally two kinds of stability that are applicable to vehicular traffic. While many terms are used in the literature [15, 16, 29], the terms used in this dissertation are *platoon stability* and *string stability*.

- **Platoon stability**: consider a finite platoon at equilibrium and imagine temporarily perturbing the lead vehicle from that equilibrium (e.g., briefly applying the brakes). This will force the following vehicles in the platoon to react to this perturbation. If the platoon is platoon stable at the given equilibrium, then the fluctuations will ultimately decay, and all vehicles will return to their initial equilibrium speed and spacing. However, if the platoon is platoon unstable at the given equilibrium, then the vehicles will continue to fluctuate in speed and spacing indefinitely.

- **String stability**: consider a semi-infinite platoon of vehicles (or a sufficiently long platoon of vehicles for practical purposes) at equilibrium flow (speed and spacing) as depicted in Figure 2.2, and consider the same ‘kick’ from equilibrium as before. If the platoon of vehicles is string stable, this perturbation will
dissipate as it propagates upstream, and if we travel sufficiently far along the platoon of vehicles, we will find a vehicle that does not experience the initial disturbance as seen in Figure 2.4. However, if the platoon of vehicles is string unstable, this disturbance will amplify as it propagates upstream as seen in Figure 2.3.

Thus, while platoon stability seeks to identify whether an individual vehicle will return to its original equilibrium configuration after a perturbation from equilibrium, string stability checks how the perturbation from equilibrium will propagate through a column of vehicles.

Since platoon unstable vehicle dynamics indicate that even a small braking event for the lead vehicle will cause the following vehicle to drive with an oscillating (non-dissipating) velocity profile, it is clear that any reasonable car following model should
In order to define traffic stability more formally, it is important to first define a notion of equilibrium. In the case of traffic flow models, we are interested in the equilibrium $\ddot{x} = 0$. Specifically, assuming a equilibrium speed function $V$, which gives the equilibrium speed-spacing relationship ($\dot{x}^* = V(s^*)$ and $s^*$), the equilibrium of a car following function $f$ is given below:

$$\ddot{x} = f(\dot{x}^*, s^*, 0) := 0. \quad (2.5)$$

In this equilibrium flow all vehicles have the same spacing $s^*$ and speed $\dot{x}_j = v^* = V(s^*) \forall j$. Note that this equilibrium may not be uniquely defined since for a given spacing, there is an equilibrium speed defined by $V$.

A linear stability analysis for string stability is applied throughout this dissertation. Therefore, for completeness, the derivation presented by Wilson and Ward [16] is reviewed in the remainder of this section. For further reading, also see [30, 31].

First, we consider small perturbations from this equilibrium state (2.5):

$$s_j = s^* + \tilde{s}_j(t) \quad (2.6)$$
and

\[ v_j = V(s^*) + \tilde{v}_j(t), \quad (2.7) \]

for small perturbations \( \tilde{s}_j(t) \) and \( \tilde{v}_j(t) \).

Linearizing \( f \) and considering the dynamics of the perturbation thus yields:

\[ \dot{\tilde{v}}_j = f_s \tilde{s}_j + f_{\Delta v} \dot{\tilde{s}}_j + f_v \tilde{v}_j \quad (2.8) \]

where the partial derivatives of \( f, f_s, f_{\Delta v}, \) and \( f_v \) are evaluated at the equilibrium \((2.5)\). Applying the definition \( \ddot{s}_j = \dot{v}_{j-1} - \dot{v}_j \) and \( \ddot{\tilde{s}}_j = \dot{\tilde{v}}_{j-1} - \dot{\tilde{v}}_j \), we get

\[ \ddot{s}_j = f_s (\ddot{s}_{j-1} - \ddot{s}_j) + f_{\Delta v} (\dot{\ddot{s}}_{j-1} - \dot{\ddot{s}}_j) + f_v (\ddot{v}_{j-1} - \ddot{v}_j), \quad (2.9) \]

which can be further simplified by applying the definition \( \Delta v := \dot{x}_{j-1} - \dot{x}_j \):

\[ \ddot{s}_j + (f_{\Delta v} - f_v) \dot{s}_j + f_s s_j = f_{\Delta v} \ddot{s}_{j-1} + f_s \ddot{s}_{j-1}, \quad (2.10) \]

which describes the dynamics of a perturbation from equilibrium through the two-vehicle pair.

We now put in place a set of \textit{rational driving constraints} (RDC) that should be satisfied by any reasonable CF model:

\[ \frac{\partial f}{\partial s} := f_s \geq 0, \quad (2.11) \]
\[ \frac{\partial f}{\partial \Delta v} := f_{\Delta v} \geq 0, \quad (2.12) \]
\[ \frac{\partial f}{\partial v} := f_v \leq 0. \quad (2.13) \]

These constraints seem reasonable since they state that all else being equal, larger spacing results in more acceleration, a larger speed difference (lead vehicle traveling faster than following vehicle) results in a larger acceleration, and at higher speeds there is a lower tendency to accelerate.
2.3.1 Check for platoon stability

With this linearization and the RDC, it is possible to first check for platoon stability by replacing the right-hand side of (2.10) with a forcing function $F(t)$ and applying a Laplace transform to consider the frequency domain:

$$S_j(z) = \frac{\mathcal{F}(z)}{z^2 + (f_{\Delta v} - f_v)z + f_s},$$

(2.14)

where $S(z)$ is the Laplace transform of $\tilde{s}_j(t)$ and $\mathcal{F}(z)$ is the Laplace transform of the forcing function $F(t)$. The growth of the solution depends on the poles $\lambda$ of the right-hand side. Specifically, to check for platoon stability, it is sufficient to compute the solutions to:

$$\lambda^2 + (f_{\Delta v} - f_v)\lambda + f_s = 0$$

(2.15)

and check the values of both solutions of $\lambda$. If both solutions of $\lambda$ have a negative real component, then the platoon in question is platoon stable. However if either or both solutions to $\lambda$ have a positive real component, then the platoon is platoon unstable.

2.3.2 Check for string stability

To check for string stability, we consider $N$ vehicles on a large ring road of length $Ns^*$. Since we are considering a ring road, it is important to enforce a periodicity to the solution such that $s_{j+N} = s_j$ (since vehicle $N+j$ is in fact vehicle $j$). This can be done by only considering decompositions of the solution into Fourier modes:

$$\tilde{s}_j = \text{Re}(Ae^{i\theta}e^{\lambda t}),$$

(2.16)

where $\text{Re}$ is the real component of the solution, $A$ is a complex constant, $\theta = 2\pi k/N$ for $k = 1, 2, \ldots, [N]$ and $0 \leq \theta \leq \pi$.

To check for string stability in a particular car following model, we simply need
to determine the growth rate $\lambda$ in terms of the wave number $\theta$. This can be done by substituting (2.16) into (2.10) which yields:

$$\lambda^2 + (f_{\Delta v}(1 - e^{-i\theta}) - f_v) \lambda + f_s(1 - e^{-i\theta}) = 0. \quad (2.17)$$

The sign of the real part of the largest solution to (2.17) governs the growth of a perturbation, and thus determines string stability of the two-vehicle interaction. This largest eigenvalue can be written as a power series:

$$\lambda_+(\theta) = i\lambda_1\theta + \lambda_2\theta^2 + i\lambda_3\theta^3 + \lambda_4\theta^4 + \ldots \quad (2.18)$$

Importantly, this solution is dominated by

$$\lambda_2 = \frac{f_2}{f_v^2} \left( \frac{f_s^2}{2} f_{\Delta v} f_v - f_s \right). \quad (2.19)$$

Thus, string stability of the platoon depends on the sign of $\lambda_2$: $\lambda_2 > 0$ implies a string unstable platoon, while $\lambda_2 < 0$ implies string stability. With further simplification under the RDC [30], assuming $f_v \neq 0$, string stability is guaranteed if:

$$0 < f_v^2 - 2f_{\Delta v} f_v - 2f_s. \quad (2.20)$$

This straightforward computation is very convenient since it can readily be applied to check for string stability of any model of the form (2.2) that satisfies the RDC.
Chapter 3

Experimental evidence for phantom traffic jams

3.1 Introduction

For many decades, the collection and interpretation of empirical traffic data has shaped our understanding of vehicular interactions and traffic flow. As a first step toward understanding the impact of AVs on traffic flow, this chapter presents a series of experiments that help us better understand the development of phantom traffic jams. These results go beyond previous experimental efforts by including on-board vehicle data that provides insight into how the formation of phantom traffic jams influence fuel consumption.

First, a historical background is provided to put this data collection effort into historical context, which helps define the specific contributions of this work. Next, a series of experiments are described, and the experimental setup as well as image processing algorithm used to extract the data is briefly outlined. Data validation is presented and some trends within the data are also presented. Much of the content of this chapter has been published in [10], where a more detailed explanation of the image processing algorithm is also provided. The data that is presented in this chapter is freely available online for research use [32] and has already proven to be
3.1.1 Background

The first major data collection effort to better understand traffic flow began with the pioneering experiments conducted by Greenshields [34] in the 1930’s, which provided an empirical model that explained the relationship between density and velocity of traffic and, consequently, the construction of the fundamental diagram. Since then, the collection of traffic data has been a critical part of transportation research. In this work, we contribute to such research efforts by providing a novel data collection method and a high-fidelity traffic dataset collected using the developed method.

Other early data collection efforts include those by researchers at General Motors (GM) who conducted many experiments to study vehicle-following characteristics in the 1950s and the 1960s [20, 21, 22, 23, 35]. For example, in 1958, GM conducted a series of experiments to test a car-following model, where a 1957 Oldsmobile was instructed to follow a lead car on a track at the General Motors Technical Center. This, and other early experiments, focused on the characteristics of single-lane car following behavior. To measure spacing, the researchers developed the GM car follower, which was a physical wire kept under tension that connected the follower and the leader and recorded the distance between the two vehicles via an oscillograph. The readings were then manually processed to produce speed and acceleration measurements. Additional experiments conducted in this period are reviewed in [29].

In the late 1960’s and 1970’s automated systems were deployed to collect aggregated data for the purpose of traffic monitoring and control in the Lincoln Tunnel [36] and traffic estimations on the Long Island Expressway in New York [37]. Today, the shape of fundamental diagrams and more broadly the aggregated or macroscopic dynamics of traffic are greatly aided by the abundance of traffic data measured from fixed sensors such as inductive loop detectors, radars, and video cameras. One prevalent traffic data source in California is the Performance Measurement System
(PeMS) database [38]. This database collects data from nearly 40,000 inductive loop detectors and toll tag readers in the state of California. Besides, the Grenoble Traffic lab instrumented a road in Grenoble, France with magnetic sensors embedded in the roadway to collect vehicle counts [39]. The Minnesota Traffic Observatory uses radar and video detectors on the I-35W/I-94 freeway to collect vehicle counts [40]. The Berkeley Highway Lab collected traffic counts using loop detectors on I-80 in Emeryville, CA [41]. Such systems typically provide vehicle counts or flows, time averaged velocities, and time averaged occupancies that enable the estimation of the traffic density.

One important limitation of aggregate traffic datasets is that they were initially introduced to collect aggregated data relevant for calibrating and validating macroscopic descriptions of the traffic flow [42, 43, 44, 45, 46]. Microscopic descriptions of traffic [47, 48, 49, 50, 51, 52] can be challenging to validate in detail without data at the level of the individual vehicle.

In parallel with the aggregated data collection efforts, early efforts aimed at measuring individual vehicle trajectories on real freeways include the work of Treiterer [53] in the 1970s. The experiments involved flying a helicopter over freeways in Ohio to photograph the traffic, which was later used to reconstruct the vehicle trajectories. The experiments by Treiterer served as the first in a series of larger efforts to collect freeway vehicle trajectories. Coifman [54] collected trajectories using a video camera on a 120 m segment of I-680 in California and observed the development of shockwaves. Other US Federal Highway Administration efforts used video footage from an aircraft to collect vehicle trajectories at six types of freeway bottleneck sections [55]. Researchers at Delft University used cameras mounted on a helicopter to collect vehicle trajectory data on a 520 m freeway segment [56] in Utrecht. The aforementioned Berkeley Highway Lab [41] and the Minnesota Traffic Observatory [40] also include efforts to extract vehicle trajectories.

Amongst the most widely used trajectory datasets are the NGSIM datasets, which were collected “in support of traffic simulation with a primary focus on mi-
The datasets contain trajectories recorded at different times on three different road segments. The first of these datasets was collected using video cameras on a 900 m segment of freeway I-80 in California over 30 minutes in December of 2003. Additionally, in April of 2005, three 15 minute data collections were performed on a 500 m segment of the same highway. Also in 2005, a 640 m segment of US-101 in Los Angeles was instrumented, and three consecutive 15 minute datasets were recorded. Several recent works have used the NGSIM data to calibrate traffic models [58, 59, 60, 61, 62, 63]. However, as pointed out in some recent works, there are limitations to this dataset since the acceleration and velocity measurements are prone to large errors [64, 65, 66], which is further magnified to a great extent by the finite difference calculation on the successive vehicle positions. Proper data collection and processing techniques are required to address these issues [65]. Other experimental efforts have been able to collect vehicle trajectories from individual vehicles in urban traffic [67, 68] and instrumented platoons of vehicles [69].

At the individual vehicle level, driver behavior has been analyzed using data collected through the naturalistic driving study (NDS) [70] by the second Strategic Highway Research Program (SHRP2). The SHRP2 data contain video footage and vehicle performance data from instrumented vehicles, and includes both a driver-facing and a forward-facing camera. The dataset contains over 42,300 hours and 2,000,000 miles of driving. The dataset includes 82 collisions and 761 near misses, which have been used to analyze driving risks [71, 72, 73]. A related naturalistic driving dataset has also been created by the University of Michigan with data for nearly one million vehicle miles traveled [74]. While these datasets provide extensive information about the instrumented vehicles, they do not include the same level of information regarding all surrounding vehicles in the traffic stream. In addition, they can only be accessed by a limited number of qualified researchers due to privacy concerns.

Moreover, in 2010, with the popularity of smartphones, the Mobile Century
project at the University of California, Berkeley collected smartphone-based GPS position data from probe vehicles on I-880 near Oakland, California [75], but only for a subset of the total vehicles in the flow.

In microscopic modelling research where a 100% penetration rate is required, the datasets collected by Sugiyama, et al. [1] and Tadaki, et al. [8] are frequently used. In order to experimentally demonstrate the development of traffic instabilities such as phantom traffic waves even without lane changes or bottlenecks, Sugiyama, et al. designed and executed a set of experiments in 2007 [1], and later in 2013 [8]. These experiments involved between 10 and 40 vehicles on a circular track. All vehicles began with a uniform velocity and spacing, but the traffic quickly develops instabilities, i.e., phantom traffic waves. These datasets are fundamentally different from the previously mentioned traffic datasets since they include data from closed-road traffic experiments as opposed to data collected on open roadways.

This dataset, and other similar datasets [8, 11, 12, 76, 77] are used for calibrating microscopic traffic flow models [11, 51, 78, 79]. For example, Jiang, et al. [11, 12, 77] collected vehicle trajectories from a platoon of 25 vehicles using GPS sensors and used the data to calibrate the parameters of the Intelligent Driver Model (IDM) [11]. However, due to the low resolution of the GPS receiver, the vehicle position accuracy is limited to 1 m.

Although the experiments conducted by Sugiyama, et al. [1, 8] provide valuable vehicle trajectories, they do not contain any information on engine performance such as fuel rate. Fuel rate data are important when studying the effects of speed oscillations on environmental factors such as emissions. Furthermore, additional open trajectory datasets under oscillatory traffic may prove useful for calibrating traffic models and designing autonomous vehicle (AV) controllers [15, 80, 81, 82, 83, 84, 85, 86, 87, 88, 89, 90, 91, 92] for driving in the presence of phantom traffic waves, or controlling the vehicle to eliminate them. To address this issue, we propose a novel data collection method and provide a high-quality dataset produced with such method. There two contributions are explained blow.
3.1.2 Contributions

We propose a novel data processing technique that achieves significantly higher spatial accuracy and temporal resolution as compared to the data collected in the seminal experiment of Sigyama, et al. [1]. Additionally, we provide a new trajectory dataset produced by this data processing method and provide the corresponding time-synchronized fuel rate data. We delineate the two contributions as follows.

The first contribution is the development of an unsupervised offline data processing technique to track the positions of multiple vehicles on a circular track. Compared to the previous data collection technique, our method is significantly more accurate and efficient. In the pioneering experiments in Sugiyama et al. [1], the position of each vehicle is accurate to within ±0.5 m at 3 Hz, yielding a velocity error of ±3 m/s (roughly 30% of the target vehicle velocity of 8.33 m/s) [27]. In a follow up experiment [8], a laser scanner is used to locate the vehicles at a 0.16 m spatial resolution and 5 Hz temporal resolution, significantly improving the accuracy compared to the earlier test. In our work, we provide a much more accurate method to extract trajectories relying only on a 360-degree panoramic camera. While the basic building blocks of the presented method consists of standard image processing methods, the algorithmic design of the system is new. The resulting trajectories are shown to have a bias of less than 0.002 m with a standard deviation of 0.11 m; the velocity has a mean error of 0.02 m/s with a standard deviation of 0.09 m/s.

The second contribution of the work is the collection of eight experimental datasets that contain accurate and high-resolution vehicle trajectories and instantaneous fuel rates. It is important to note that accurate datasets for complex real-highway situations already exist (such as NGSIM), but certain research tasks (e.g., developing car-following models) can benefit from datasets that remove much of the noise associated with highway traffic and contain the occurrence of traffic waves caused by car-following dynamics. This study provides such a dataset. Moreover, the added fuel consumption data opens up the opportunity to study the precise relationship between traffic dynamics and fuel economy. The high accuracy and res-
olution of the trajectory data also provide valuable resources to study characteristic human driving behaviors at a temporal resolution of less than a tenth of a second.

The content of this chapter can be used for a variety of transportation research initiatives, including traffic stability analysis, microscopic model calibration, and fuel consumption modeling. It has already served as the basis for two derivative research projects: the method deployed in this paper has been applied to study the ability of a single autonomous vehicle to regulate oscillatory traffic flow [13] as well as to investigate the impacts of phantom traffic waves in fuel efficiency and engine performance [14].

However, it is important to acknowledge that the experimental setup, the proposed data processing technique, and the published dataset come with limitations. The single-lane closed-loop circular track is not a realistic representation of all real-world traffic phenomenon. For example, it does not include lane changing events, intersection conflicts, or low density flows. Additionally, the data processing method is not designed for deployment in real-time and complex urban environments, but rather for data collection in an experiment.

3.2 Experiments

A total of eight experiments were conducted in Tucson, Arizona in July 2016. The goals of these experiments were two-fold: (i) to develop and test a method to extract high quality trajectory and fuel consumption data of vehicles in phantom traffic jams; and (ii) to investigate the extent to which a single vehicle (equivalent to a low penetration rate of vehicles on a freeway), driving differently from the remaining traffic, is able to change the traffic state. The main results of goal (i) are presented in the present work. Regarding goal (ii), in this work we provide preliminary evidence that a single vehicle is able to influence the flow, and note that the main experimental findings to support this objective are available Chapter 5. In Chapter 5, additional experiments are conducted following the same setup described
in the present chapter, but with the modification that a carefully controlled single autonomous vehicle is used to dissipate the phantom traffic jam when it appears. Each experiment is labeled with a letter from A to H, in the order they occurred. In each experiment drivers were given specific instructions on how to drive. The experimental setup is briefly outlined in Section 3.2.1 and the experimental protocol is summarized in Section 3.2.2.

3.2.1 Experimental setup

To test the performance of the proposed data processing method on a circular track, we re-created the results observed in the Sugiyama, et al. experiment [1] with an additional step of instrumenting each individual vehicle with a OBD-II scanner. Some experimental changes were made (track size, direction of driving) to account for larger and right-hand drive vehicles in the US compared to Japan. The track was available for a total of four hours for experimentation. Taking driver rest breaks and a driver briefing into account this allowed for three hours of testing. The time to re-set the track after each experiment was approximately 15 minutes, and each experiment lasted between five and 10 minutes.

The experiments are divided into two sets (see Table 3.1). In Experiments A-E, we used instruction I for which each driver is instructed to “safely follow the vehicle in front as if in rush hour traffic,” and varied the density by changing the number of vehicles on the road. We visually observe that some vehicles drive very conservatively (e.g., by leaving excessive gaps) which dampened any waves that might arise. Consequently, we changed the driving instructions of all drivers to instruction II in Experiments F, G, and H, for which drivers were instructed to “drive by the same instructions as before, but in addition place an emphasis on closing the gap the the vehicle in front, whenever safety permits.” Specifically, the instructions were given as follows:

- **Instruction I:** *Drive as you would if you were in rush hour traffic. Follow the vehicle ahead without falling behind. However, drive as safely as would on*
the road. Do not pass the car in front of you. Do not hit the car in front of you.

• **Instruction II:** Drive as if you were in rush hour traffic. Follow the vehicle ahead without falling behind. Do not pass the car ahead. Do not hit the car ahead. Drive safely at all times. Do not tailgate. But put an emphasis on closing up to the vehicle ahead, if a gap starts opening up.

Additionally, for Experiments G and H we instructed one driver (co-author M. Bunting, a member of experimental staff) to change his driving behavior during the experiment to observe the effect that a single vehicle has on the overall traffic flow.

The experiments were conducted on a circular track 260 m in circumference. The track length was selected to approximate the total unoccupied road space of the experiments conducted by Sugiyama et al. [1]. The main reason behind this experimental design was to induce phantom traffic waves. The induced phantom traffic waves are more interesting than freeflow or congested traffic, since the dynamics of phantom traffic waves are not as well understood as the dynamics of free flow and congestion. A phantom traffic wave will form when the average density is around 7 m/veh, as was shown in [1]. If the unoccupied space is too large, there may never be a phantom traffic wave. On the other hand, if the unoccupied space is too little, the traffic will be stuck in congestion.

The track was constructed on a large paved parking lot at the Tucson Dragway in Tucson, Arizona, and selected for its smooth, even surface, and abundance of open space. The experimental track with vehicles is shown in Figure 3.1a. The inside edge of the track was marked with short orange cones. Additional cones were used to mark the pre-measured location of the front tire of each car to ensure uniform spacing at the start of the experiment.

The vehicles used for this experiment were procured from the University of Arizona’s motor vehicle pool. The year, make, model, length, and nominal EPA-reported fuel rate of each vehicle used in the experiment is presented in Table A.1. The vehicles used in each experiment is given in Table A.2.
<table>
<thead>
<tr>
<th>Exp. No.</th>
<th>No. of vehicles</th>
<th>Instruction</th>
<th>Density (veh/m)</th>
<th>Duration (s)</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>20</td>
<td>I</td>
<td>13.00</td>
<td>416</td>
</tr>
<tr>
<td>B</td>
<td>20</td>
<td>I</td>
<td>13.00</td>
<td>442</td>
</tr>
<tr>
<td>C</td>
<td>22</td>
<td>I</td>
<td>11.82</td>
<td>388</td>
</tr>
<tr>
<td>D</td>
<td>21</td>
<td>I</td>
<td>12.38</td>
<td>480</td>
</tr>
<tr>
<td>E</td>
<td>19</td>
<td>I</td>
<td>13.68</td>
<td>333</td>
</tr>
<tr>
<td>F</td>
<td>19</td>
<td>II</td>
<td>13.68</td>
<td>175</td>
</tr>
<tr>
<td>G</td>
<td>21</td>
<td>II</td>
<td>12.38</td>
<td>587</td>
</tr>
<tr>
<td>H</td>
<td>22</td>
<td>II</td>
<td>11.82</td>
<td>545</td>
</tr>
</tbody>
</table>

Table 3.1: Summary of experiments.

3.2.2 Experimental protocol

Each experiment consisted of the following phases: (i) setup; (ii) evacuation; (iii) initialize; (iv) drive; (v) stop; (vi) conclusion.

During each phase, the following items were performed.

(i) Setup: Vehicles are distributed equally according to the spacing of their front-left tire. Drivers are individually instructed to turn on their in-vehicle OBD-II scanners. Additional driver instructions (if any) are delivered to individual drivers through the window. The panoramic camera is switched on.

(ii) Evacuation: All research team personnel evacuate the track.

(iii) Initialize: An air horn sounds to instruct all drivers to switch gears from “park” to “drive,” without moving.

(iv) Drive: An air horn sounds, to instruct all drivers to begin driving.

(v) Stop: An air horn sounds, instructing drivers to come to a safe stop and switch gears into park.

(vi) Conclusion: Experiment personnel enter the track after all vehicles have stopped. Drivers are individually instructed to turn off their in-vehicle OBD-II scanners. The central camera is switched off.
3.2.3 Experimental instruments

Each vehicle in the experiment was instrumented with an OBD-II scanner to collect vehicle data during the experiments. All vehicles sold in the United States after 1996 are required to provide vehicle performance data from the engine control unit (ECU) via an OBD-II port. The OBD-II data were logged using a ScanTool OBDLink LX scanner. The data provided through the OBD-II port included vehicle dynamics data such as engine speed, vehicle speed, and fuel rate as well as diagnostics data such as sensor voltage of a variety of vehicle sensors, which can be used to identify vehicle malfunction. While the OBD-II data format is standardized, due to different vehicle configurations and vehicle ages, not all vehicles reported the same data through OBD-II.

A VSN Mobil V360 panoramic video camera was used to record the motion of the vehicles, and was located at the center of the track. It has 360° horizontal field of view and 60° vertical field of view, recording at a resolution of 3840 × 640 pixels at a sampling rate of 30 Hz. The high spatial and temporal resolution of the panoramic camera enabled precise tracking of the dynamics of the vehicles in the scene. The proposed vehicle tracking algorithm is described next.
3.3 Methodology

Data is collected using a 360-degree panoramic camera located at the center of the track. To convert the video data into vehicle trajectories, a five-step pipeline is constructed. The pipeline is briefly described below. More details on the image processing technique used are available in [10].

1. **Background subtraction**: In this step, an estimate of the background is obtained over a sequence of frames of the video. The process of estimating the background is complicated by the facts that (i) the vehicles occlude the background scene, (ii) occasionally vehicles stop (i.e., in a phantom traffic wave), making them difficult to differentiate from the stationary background using motion-based methods, and (iii) occasionally the background changes or moves (e.g., due to changes in light intensity or the motion of clouds). Consequently, we adopt a strategy that first detects sufficiently stationary pixels in each frame (described in detail below), and we estimate the background as the median pixel value over the set of images. For an individual pixel location, the median of the non-moving pixels provides a reasonable estimate of the background pixel value as long as the majority of frames in which the pixel is stationary do not correspond to a vehicle. This condition is met in our experiments by choosing a time horizon to estimate the background which is sufficiently large relative to the duration over which vehicles are stopped in the phantom traffic wave.

2. **Object identification**: After the background has been subtracted (i.e., pixel-wise and channel-wise subtraction) from every frame, we proceed next to construct a template of each vehicle which can be tracked from one background subtracted frame to the next. A high quality template of each vehicle is constructed on a single frame by first clustering the foreground pixels into vehicles, and then enhancing each vehicle cluster, e.g., by filling in holes. We
note that keeping the vehicle template static works the best (compared to
allowing the template to be adjusted as time progresses) in our experience,
because it prevents the templates from being polluted by random noise. The
quality of tracking can degrade substantially if the quality of input template
is not maintained.

3. Object tracking: Object tracking in this application is the procedure to deter-
mine the locations of the vehicles over time. This objective can be achieved by
means of frame-by-frame matching of the vehicle template to the foreground
image. More precisely, the vehicle template is matched to a transformed im-
age in which the background image has been subtracted and the resulting
foreground noise is reduced using morphological operations. In the object
tracking step, the RGB images are converted to a scalar greyscale quantity,
so that standard implementation libraries (i.e., OpenCV [93]) can be used
directly.

4. Noise reduction: To improve the quality of the data generated from the track-
ing algorithm, a basis spline (B-spline) noise reduction method is applied. We
first describe the major types of noise observed in the dataset, and then the
smoothing technique used to reduce the noise.

3.4 Validation

The tracking algorithm described in Section 3.3 is validated both in terms of posi-
tional accuracy and in terms of velocity accuracy. Position estimates are compared
with a manually labeled dataset, while the velocity data are validated by comparing
to high-precision velocity data recorded on the highly instrumented University of
Arizona Cognitive and Autonomous Test Vehicle (CAT Vehicle), which is vehicle
number 20 in each experiment. Due to the lack of validation datasets for these
measurements, only the distribution of vehicle accelerations and fuel rate are also
presented. Finally, the choice of hyperparameter tolerance in the spline smoother is validated through a parameter sweeping scheme.

3.4.1 Position accuracy

We compare the positions estimated from the image processing algorithm with manually labelled position data. Manual labels are generated through three human annotators using an online annotation tool, LabelMe [94]. The annotators were asked to label the rear bumper location of vehicle 19 and the front bumper location of vehicle 20. One annotator labeled frames at a framerate of 3 Hz, for a total of 900 frames (five minutes) of Experiment A. Two additional annotators were instructed to independently label the first 30 seconds of the experiment at the same frame rate, so that the inter-annotator agreement can be computed for the three annotators. The sample standard deviation of the position labels is 0.05 m (about $\frac{3}{4}$ pixels). Consequently the human annotation data can be used as a reasonable proxy of the true position of each vehicle.

The position data extracted from the camera are compared on the 900 frame dataset using both the raw and the smoothed camera trajectory data of vehicle 19 and 20. We treat the human annotated position estimates as the true position of the vehicle, from which error residuals and the standard deviation of the error distribution can be computed. The average error of the raw camera position estimates is -0.04 m, and the standard deviation of the errors is 0.12 m. The average error of the smoothed camera trajectory is less than 0.002 m, and the errors have a standard deviation of 0.11 m. The error distributions of the raw and noise-reduced position estimates are shown in Figure 3.2.

3.4.2 Velocity accuracy

The accuracy of the smoothed camera velocity estimate is compared to the velocity recorded from an odometry sensor on vehicle 20 (the highly instrumented CAT Vehicle) in Experiment A. In the following discussion, we treat the odometry data
from the CAT Vehicle as the true velocity signal from which errors are computed. We also compare the velocity recorded directly from the ScanTool OBDLink LX OBD-II scanner installed on all vehicles in the experiment (including the CAT Vehicle). Since the odometry-based velocity readings are recorded at 20 Hz, the 30 Hz camera data are downsampled from 30 Hz to 20 Hz for point by point comparison.

The difference between the raw camera signal and the smoothed camera signal for Experiment A is illustrated in Figure 3.3. The effects of B-spline smoothing is demonstrated in Figure 3.3a, while the accuracy of the raw and smoothed camera velocity is shown in Figure 3.3b. In Figure 3.3a, the raw camera velocity contains clear quantization errors with a step size of about 2.03 m/s, while the smoothed camera velocity is free of the quantization errors. Irregularly large estimates, or burst noises, in the raw camera velocity such as 8.12 m/s and -2.03 m/s are also removed in the smoothed data. As evident in Figure 3.3b, the noise reduction technique converts the original noisy measurements to one that is one to two orders of magnitude closer to the odometry velocity.

In Figure 3.4, the error distributions of the raw camera velocity, the OBD-II recorded velocity, and the smoothed camera velocity for vehicle 20 in Experiment A are shown. The smoothed camera velocity error distribution has a standard deviation (0.09 m/s) that is an order of magnitude smaller than the raw camera data (1.17 m/s), and it is also smaller than the OBD-II velocity error standard deviation.
(a) Comparison of velocity signals for vehicle 20 in Experiment A. The raw camera speed signal (green), quantized into integer multiples of 2.03 m/s oscillates around the smoothed camera velocity signal (red).

(b) Validation of velocity signals for vehicle 20 in Experiment A. Here the odometry velocity signal is selected as the reference. The difference between raw camera velocity signal and the reference is shown in blue, while the difference between the smoothed velocity signal and the reference displayed in red.

Figure 3.3: Analysis on B-spline smoothing for noise reduction. The time series plot shows the effects of the B-spline smoother. The residual plot illustrates that the noise reduction method significantly improves the data quality.

(0.37 m/s). The surprising finding that the camera speeds are more precise is due to the (undocumented) internal processing of the OBD-II signal that occurs either on the vehicle or in the OBD-II scanner. From Figure 3.5, we observe that the OBD-II recorded velocity is also quantized, and appears to hold the value of the recorded velocity constant over several seconds. This leads to larger errors than the smoothed camera velocity data.

3.4.3 Acceleration and fuel rate distribution

Due to the lack of other reliable measures against which the collected data can be validated, we are only able to show that the distribution of the accelerations and fuel rate data are physically plausible (e.g., the accelerations lie within the bounds of the physical performance limits of the vehicles). The distribution of acceleration measurements for all vehicles in Experiment A is shown in Figure 3.6a, and the distribution of fuel rate measurements is shown in Figure 3.6b. For common commercial vehicles, the magnitude of acceleration is less than 5 m/s^2 and the limit
(a) Distribution of difference between raw velocity and odometry velocity. (b) Distribution of difference between OBD-II velocity and odometry velocity. (c) Distribution of difference between smoothed camera velocity and odometry velocity.

Figure 3.4: Results of validation analysis on the speed measurements in Experiment A.

(a) Comparison of velocity signals for vehicle 20 in Experiment A. The OBD-II recorded speed signal (green) is quantized in time and space. (b) Validation of velocity signals for vehicle 20 in Experiment A. Here the odometry velocity signal is selected as the reference. The difference between OBD-II velocity signal and the reference is shown in blue, while the difference between the smoothed velocity signal and the reference displayed in red.

Figure 3.5: Comparison between smoothed camera velocity data and OBD-II velocity data.
The collected dataset is shown to comply with these limits. In fact, the magnitude of acceleration rarely exceeds $1.5 \text{ m/s}^2$, and the fuel rate rarely exceeds $8 \text{ l/h}$. The distributions of acceleration and fuel rate for the other experiments are similar to those of Experiment A, and are collectively summarized in Table 3.2b.

### 3.4.4 Noise reduction parameters selection

Note that the results presented above are not sensitive to the tolerance parameter of the B-spline smoother. Figure 3.7a shows the result of a sensitivity analysis, which illustrates that any tolerance value between 11 m and 17 m produces small error standard deviations in position data and velocity data. Figure 3.7b indicates that the estimation bias in the position and velocity data are also minimized when the tolerance is between 11 m and 17 m. Consequently the tolerance parameter is set to be 14 m, which lies in the center of the optimal interval. Recall that the tolerance controls the cumulative error between the raw data and the B-spline, and indirectly controls the window (number of points fit with a single spline). When the tolerance is set to 14 m, the window typically contains hundreds or thousands of points.

Moreover, it is shown in Table 3.2 that the specific choice of the smoother parameter in Experiment A generalizes well to the other experiments. Specifically, we apply the optimal smoother parameter from experiment A to the remaining ex-
Figure 3.7: Results of parameter tuning using the position labels and odometry measurements in Experiment A.

Experiments, which were not used to determine the optimal parameter. Under the threshold choice of 14 m, the maximum (over all tests) mean error is 0.03 m/s with a standard deviation of 0.11 m/s of smoothed velocity error mean is 0.02 m/s, and the maximum ranges of smoothed velocity error standard deviation is 0.03 m/s. Therefore the selected smoother parameters generalize well to other experiments and the high quality velocity estimates are not an artifact of overfitting the tolerance parameter on a single dataset.

3.4.5 Data anomalies

Although the data collected from the experiments presented in this chapter are largely complete, there are a few anomalies that must be noted. These take the form of missing or erroneous measurements in the OBD-II data.

Concretely, the OBD-II fuel rate data (l/h) contain missing entries, zero readings, and an inconsistency in sampling rate. OBD-II data are missing from the following vehicles: Experiment D, vehicles 5 and 6; Experiment E, vehicle 3; Experiment F, vehicle 17; Experiment H, vehicle 4. Zero fuel rate readings are recorded for vehicle 15 in Experiment A for the first four seconds of the experiment. These missing data entries and zero readings are the result of operational errors with the OBD-II scanners during the experiment. Additionally, while the experiments are
Table 3.2: Summary of validation analysis on velocity, acceleration and fuel rate data. The velocity error for is defined to be the difference between the velocity measure of interest \(v\) and the odometry velocity readings \(v_{odo}\), i.e., \(v - v_{odo}\). *The abnormal zero fuel rate readings recorded from vehicle 15 at the start of experiment A are excluded from the calculation.

designed to collect OBD-II data at the maximum sampling rate of 20 Hz, the OBD-II scanner in vehicle 19 collected data at 10 Hz for all experiments due to an incorrect setting in the OBD-II logger.

### 3.5 Datasets

A summary of the data collected is first provided in Table 3.3. Each experiment is then described with details, and followed next by a qualitative discussion of the experiment results. For a visual presentation of the data, please refer to Figure A.1 through Figure A.8 in Appendix A.

#### 3.5.1 Summary statistics

In Table 3.3, the experiments are compared with respect to a number of quantitative measures.
To quantify the velocity variability (which is used as a measure of the wave strength), the velocity standard deviation for critical intervals in each test is presented. Precisely, the wave strength is quantified as the standard deviation of the \( m \) velocity measurements (per vehicle) from \( n \) vehicles over a time interval. Let \( v^i_t \) denote the \( t^{th} \) velocity measurement from vehicle \( i \). The velocity standard deviation is computed as

\[
\sigma_v = \left( \frac{1}{mn-1} \sum_{t=1}^{m} \sum_{i=1}^{n} (v^i_t - \bar{v})^2 \right)^{\frac{1}{2}},
\]

where \( \bar{v} \) is the average velocity defined by:

\[
\bar{v} = \frac{1}{mn} \sum_{t=1}^{m} \sum_{i=1}^{n} v^i_t.
\]

Similarly, the average fuel rate \( \bar{r} \) and fuel rate standard deviation \( \sigma_r \) is also computed for each test.

For experiments A-E, the quantities are computed over the full experiment duration minus an initial period where the vehicles were accelerating from rest. In Experiments F–H, a single vehicle was commanded to reduce the speed (Experiment F) or to maintain a target speed (G and H). In these tests, the relevant quantities are computed both prior to the intervention and after the intervention.

### 3.5.2 Experiment descriptions

In Experiment A, 20 vehicles were deployed on the 260 m track, and instruction I was given to the drivers. The vehicle trajectories are shown in Figure A.1, where small traffic waves are observed. The average speed was 3.11 m/s with a velocity standard deviation of 0.80 m/s, and the average fuel rate was measured to be 2.46 l/h/veh. The experiment ended after 416 seconds.

Experiment B was conducted with the same vehicle density and instruction as Experiment A. The resulting traffic was slightly slower and less oscillatory than in Experiment A. The waves are shown in Figure A.2, where the average speed was
<table>
<thead>
<tr>
<th>Exp.</th>
<th>No. of veh.</th>
<th>Instruction</th>
<th>$\bar{v} \pm \sigma_v$ before intervention (m/s)</th>
<th>$\bar{v} \pm \sigma_v$ after intervention (m/s)</th>
<th>$\bar{r} \pm \sigma_r$ before intervention (l/h/veh)</th>
<th>$\bar{r} \pm \sigma_r$ after intervention (l/h/veh)</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>20</td>
<td>I</td>
<td>3.11 ± 0.80</td>
<td>n/a</td>
<td>2.46 ± 1.07</td>
<td>n/a</td>
</tr>
<tr>
<td>B</td>
<td>20</td>
<td>I</td>
<td>2.81 ± 0.69</td>
<td>n/a</td>
<td>2.36 ± 0.92</td>
<td>n/a</td>
</tr>
<tr>
<td>C</td>
<td>22</td>
<td>I</td>
<td>2.37 ± 0.55</td>
<td>n/a</td>
<td>2.23 ± 0.80</td>
<td>n/a</td>
</tr>
<tr>
<td>D</td>
<td>21</td>
<td>I</td>
<td>3.15 ± 0.70</td>
<td>n/a</td>
<td>2.51 ± 1.04</td>
<td>n/a</td>
</tr>
<tr>
<td>E</td>
<td>19</td>
<td>I</td>
<td>3.88 ± 0.91</td>
<td>n/a</td>
<td>2.62 ± 1.21</td>
<td>n/a</td>
</tr>
<tr>
<td>F</td>
<td>19</td>
<td>II</td>
<td>7.68 ± 0.96</td>
<td>5.79 ± 1.91</td>
<td>3.90 ± 2.34</td>
<td>3.58 ± 2.63</td>
</tr>
<tr>
<td>G</td>
<td>21</td>
<td>II</td>
<td>5.27 ± 2.63</td>
<td>5.81 ± 1.28</td>
<td>4.21 ± 3.28</td>
<td>3.67 ± 2.66</td>
</tr>
<tr>
<td>H</td>
<td>22</td>
<td>II</td>
<td>5.07 ± 2.46</td>
<td>4.51 ± 1.89</td>
<td>4.14 ± 3.04</td>
<td>3.47 ± 2.60</td>
</tr>
</tbody>
</table>

Table 3.3: Summary of experiments conducted. $\bar{v}$ is the average velocity, $\sigma_v$ is the velocity standard deviation, $\bar{r}$ is the average fuel rate, and $\sigma_r$ is the fuel rate standard deviation.

2.81 m/s, velocity standard deviation was 0.69 m/s. The fuel rate in this experiment was 2.36 l/h/veh. This experiment ended after 442 seconds.

The vehicle density increased from 20 vehicles to 22 vehicles in Experiment C, while maintaining the same driver instruction as before. The resulting traffic was both slower and had lower velocity standard deviation than both Experiments A and B. The traffic in Experiment C (shown in Figure A.3) had an average velocity of 2.37 m/s, and a velocity standard deviation of 0.55 m/s. The average fuel rate in this experiment was 2.23 l/h/veh, which was also lower than both Experiment A and B where the vehicle density was lower. The experiment ended after 388 seconds.

Experiment D conducted with 21 vehicles, and the average speed and velocity standard deviation increased with respect to experiment C. The average speed was 3.15 m/s, and the velocity standard deviation was 0.70 m/s. In this experiment, a higher fuel rate than in the previous experiment of 2.51 l/h/veh was observed. The resulting vehicle trajectories can be seen in Figure A.4. The experiment ended after 480 seconds.

The last experiment conducted with instruction I was Experiment E. This experiment had the lowest vehicle density with 19 vehicles on the track. The result
was faster moving traffic with stronger waves as seen in Figure A.5. The average velocity in this experiment was 3.88 m/s and the velocity standard deviation was 0.91 m/s. This was the fastest and most oscillatory traffic observed when instruction I was used. This also resulted in Experiment E having the highest fuel rate of all experiments that used instruction I, with a fuel rate of 2.62 l/h/veh. The experiment ended after 333 seconds.

To contrast the effect on the development of traffic waves of the instructions given to drivers, Experiment F was also conducted with 19 vehicles on the track. However, different from Experiment E, in Experiment F, drivers were given instruction II. In this case, a larger velocity standard deviation was observed compared to the experiments in which instruction I was given, as seen in Figure A.6. The average velocity over the first 59 seconds of the experiment was 7.68 m/s, nearly twice the velocity in any of the previous experiments. Due to the substantial speed increase, the driver of the CAT Vehicle (vehicle 20) was told via radio to slow down the traffic. The result of this was a slowdown of all vehicles on the track, as seen in Figure A.6. The average velocity standard deviation over the first 59 seconds was 0.96 m/s and the fuel rate over the same interval was observed to be 3.90 l/h/veh. Since the slowdown invention amplified strong stop-and-go wave, to avoid the wave be amplified beyond the safe range, the experiment was ended after only 175 seconds.

Experiment G was conducted with 21 vehicles on the track, using instruction II. The resulting traffic waves were larger than those in Experiment F, and significantly more pronounced than the oscillations observed in Experiments A through E. The average speed was 5.27 m/s (velocity standard deviation of 2.63 m/s) and the fuel rate was 4.21 l/h/veh over the first 312 seconds of the experiment. At this point, the driver of the CAT Vehicle was again instructed to drive with a constant speed, this time of 6.26 m/s (specifically, the command to drive at 14 mph was given, since a US vehicle was used). However, due to the limits in the precision of human driving behavior, this speed was not strictly maintained by the CAT Vehicle. After the intervention the velocity standard deviation decreased by more than a half to 1.36
m/s. This indicates that a single vehicle may be able to reduce the speed variability of the flow. This is seen in Figure A.7. The experiment ended after 587 seconds.

To further explore the difference in wave development under instructions I and II, Experiment H was conducted with instruction II and 22 vehicles on the track. The average speed in the first 191 seconds of the experiment was 5.07 m/s, the velocity standard deviation was 2.46 m/s, and the average fuel rate was 4.14 l/hr/veh. As with Experiment G compared to D, Experiment H compared to C had significantly larger waves, and a significantly higher fuel rate due to the change in the instructions. Again as in Experiment G, the driver of a single vehicle was instructed to maintain a constant after some time. In the case of Experiment H, this occurs twice: first after 191 seconds when the driver of the CAT Vehicle was instructed to drive at 5.36 m/s (12 mph), and after 411 seconds, when the driver of the CAT Vehicle was instructed to reduce the speed to 4.47 m/s (10 mph). The influence of this intervention on the vehicle speeds and vehicle trajectories is observed in Figure A.8. The velocity standard deviation while the CAT Vehicle was intervening is lower than in the first portion of the experiment. Experiment H ended after 545 seconds.

Note that the interventions in Experiment G and H were different from the intervention in Experiment F. In Experiment F, the driver was instructed to slow down the traffic, while in Experiment G and H, the driver was instructed to maintain a constant velocity. This resulted the distinct effects of interventions as shown in Figure 3.8a: The Experiment F intervention amplified the wave while the Experiment G and H interventions dampened it.

3.5.3 Qualitative observations

The general trends observed in the data are outlined as follows: (i) the instructions given to drivers make a significant difference on the magnitude of waves; (ii) when instruction I was given, over the range of densities explored, lower density results in stronger waves (measured as the instantaneous velocity standard deviation of all vehicles averaged over the duration of the experiment); and (iii) stronger waves
result in a higher fuel rate.

The velocity standard deviation depends strongly on the instructions given to the drivers. This is seen in Figure 3.8a, where the blue circles represent experiment runs in which drivers were given instruction I and instructed to, “follow the vehicle in front and drive as if you were in rush hour traffic,” while the red stars are trials where drivers were given instruction II and told to “place an emphasis on closing the gap with the vehicle in front.”

Compared to experiments with instruction I, on average stronger waves appeared in experiments with instruction II. This indicates that aggressive driving behavior will induce greater velocity variations, causing the traffic to exhibit speed oscillations.

In instruction I, the intensity of traffic waves observed also depends on the vehicle density. The relationship between the number of vehicles and the intensity of the waves as measured as velocity standard deviation is seen in Figure 3.8a. This shows a general negative correlation between the number of vehicles on the track, and the intensity of the waves observed when instruction I is given.

The effect of traffic waves on the vehicle fuel rate is seen in Figure 3.8b, where a clear increasing trend is observed between the velocity standard deviation and the average fuel rate. This result indicates that oscillatory traffic with a high velocity standard deviation is bad from a fuel rate standpoint.

3.6 Conclusion

This chapter describes a set of eight experiments in which 19 to 22 vehicles drive in a ring and traffic waves emerge. Trajectory data are extracted via an offline image processing algorithm that produces accurate trajectories. The produced trajectory data are very accurate: the mean position bias is less than 0.002 m with a small standard deviation of 0.11 m as compared to human-labeled data. The derived velocity estimates are also reliable: the mean velocity biased is only 0.02 m/s with
(a) Wave strength as a function of the number of vehicles on the circular track showing: (i) instruction II on average generates stronger waves (measured by velocity standard deviation) than instruction I; and (ii) generally decreasing wave strength with increasing vehicle density for instruction I.

(b) Fuel rate as a function of wave strength indicating that when stronger traffic waves (greater velocity standard deviation) are present, vehicles consume more fuel.

Figure 3.8: Summary of experiments depicting: (i) a general decreasing trend in wave strength as number of vehicles on the track increases for instruction I, and increasing wave strength with number of vehicles for instruction II, (ii) on average instruction II generates stronger waves (greater velocity standard deviation) than instruction I, and (iii) an observed increase in fuel rate with wave strength. * The intervention in F was to slow down the traffic as opposed to maintain a constant speed in G and H. Because wave was amplified after the intervention, Experiment F was ended very quickly due to safety concerns.
a small standard deviation of 0.09 m/s. Additionally, each vehicle is instrumented with an OBD-II scanner to log the fuel rate throughout each experiment, providing a link between traffic waves and fuel consumption.

The produced trajectory and fuel rate data are an asset to the transportation research community. They directly support many types of empirical research including microscopic model calibration, studying driving behavior, fuel consumption modelling, and vehicle emission modelling. In the interest of research reproducibility and open access, we have made the data and the Python implementation of the tracking algorithms freely available online [97].
Chapter 4

Adaptive cruise control and phantom jams

4.1 Introduction

As demonstrated in the previous chapter, human driving behavior alone is sufficient for phantom traffic jams to arise. One approach to prevent these phantom jams from arising is to use connectivity and longitudinal vehicle control to form string stable vehicle platoons. Before vehicles are fully autonomous, adaptive cruise control (ACC) are the first step toward an autonomous future. Much like fully autonomous vehicles, ACC vehicles are capable of longitudinal control. However, a key distinction is that the human driver is constantly monitoring the longitudinal control as well as steering the vehicle. These vehicles are already becoming commonplace on our roadways, and understanding their impact on traffic stability is a critical step to understand the stability of traffic under AV control. This chapter outlines a series of experiments conducted with ACC vehicles to understand how these vehicles influence traffic stability.

First a brief overview of previous efforts to understand the stability of ACC systems is presented. Then a series of experiments are described, that provided data to provide system identification, which is next described. The stability of the
calibrated ACC model is analyzed, and simulation results are used to show that current ACC systems are unstable, but small modifications can be made to stabilize the traffic. Many of the results presented in this chapter are currently under review for publication [98].

4.2 Background on ACC stability

Interest in platoons of string stable vehicles has existed for a while and it has been known that adding connectivity can guarantee stability and prevent phantom jams from arising within the platoon. This has been demonstrated both in theory [15, 84, 87, 88, 90] and experimentally [85, 86, 89, 91].

More recently there has been interest in how a small number of AVs are able to achieve string stability of a platoon even if not all vehicles in the flow are autonomous or have connectivity (e.g., mixed human and autonomous flows). This too has been considered both in theory [80, 81] and experimentally [13, 99]. In [13], a single autonomous vehicle in a stream of 20 human-piloted vehicles was able to stabilize the traffic flow and dampen stop-and-go waves. Recently, Jin, et al. [99] demonstrate experimentally that substantial improvements in fuel efficiency and safety may be achieved when only some vehicles use connected ACC.

Before vehicles become fully autonomous, it is likely that we will start to see an increasing number of vehicles with partially-autonomous and driver assistance features [100]. These features include ACC, which have been shown in theory to be capable of stabilizing the traffic flow at a market penetration rate (MPR) as low as 20% [80].

While ACC vehicles (without connectivity) have traditionally been considered a premium feature in luxury vehicles, more recently they have become a standard feature on many commercially available vehicles in the US. As stated earlier in Chapter 1, through the second quarter of 2018, 16 of the 20 best selling cars in the US are available with ACC, and several of them come equipped with ACC as a
standard feature [101]. This indicates the extent to which ACC vehicles are likely to become a common sight on US highways, and therefore it is crucial to have a better understanding of the traffic stability implications of ACC vehicles that are now commercially available.

In the early work [102], a methodology is proposed and applied to commercially available vehicles and by instrumenting them with differential GPS receivers to collect relevant positioning and speed data. After conducting a series of experiments on three commercially available ACC equipped vehicles in 2003, the work concluded, “Based on measured characteristics of ACC systems, simulation analyzes indicate that currently-available ACC-equipped vehicles will have string-performance qualities that are characterized by substantial overshoots in velocity and range clearance in response to changes in the velocity of the preceding vehicle” [102]. More recently in 2014, Milanés et al. [103] instrumented a platoon of commercially-available ACC vehicles and collected experimental data that also indicated the tested ACC system was string unstable.

Our present work builds on the previous efforts [102, 103] to characterize the stability of commercially-available ACC systems and addresses the question of whether modern systems are also unstable. Our main result is to show that even as ACC systems become more prevalent in commercially-available vehicles, there still exist modern ACC systems that are not string stable under all driving settings. Specifically, this chapter presents preliminary experimental results from a series of tests with a fleet of seven commercially-available ACC-capable midsize sedans. Using the collected data, a car-following model is used to describe the ACC dynamics of each vehicle and then calibrated to fit the data. The calibrated model is used to analyze stability of the tested ACC vehicle. Given the sparsity of experimental work on the stability of commercially available ACC vehicles, this chapter provides additional preliminary evidence that the latest ACC systems need further investigation to characterize their impacts on phantom traffic jams. We caution the reader that the results presented here do not indicate whether or not ACC vehicles perform better
or worse than human drivers, which may also have string unstable dynamics [1].

4.3 ACC dynamical model and stability analysis

In this section modeling and analysis techniques are introduced that allow for the simulation and stability analysis of ACC-equipped vehicles. We first review a simplified ACC model used in [103, 104], which is used in this work due to the previously reported quality of fit for ACC vehicles. Using a linear stability analysis we calculate the parameter regimes under which the ACC model is string stable and string unstable, following the analysis of Wilson and Ward [16], see Chapter 2 for a review. A brief numerical example shows the impact of the stability on the behaviour of a platoon of ACC engaged vehicles.

4.3.1 ACC Model

In general, vehicle dynamics and control can be complex and difficult to replicate in simulation. The controllers may be implemented with logic determined by the vehicle state and environment [102], and depend on factors such as the engine RPM, the engine temperature, and the road grade. As such, approaches to completely replicate the exact control logic on vehicles may be very difficult if not impossible without exact information about the internal vehicle state. Moreover, it may not be necessary to characterize the overall impacts of the ACC system on traffic flow stability. Consequently, we employ a car following model of an ACC engaged vehicle, which models the vehicle dynamics and ACC system as a single system. The model shows good performance when reconstructing the observed behavior of the ACC systems in field tests. The benefits of this simple model are that is easy to analyze and accurately calibrate to field data.

Specifically, we consider the response of a following vehicle with adaptive cruise control engaged in response to a lead vehicle in front. The adaptive cruise control is considered to be a behavioral rule that governs the acceleration, $\ddot{x}(t)$, of the following
vehicle and is of the general form presented in Chapter 2:

\[ \ddot{x}(t) = f(s, v, \Delta v), \quad (4.1) \]

where \( s \) is the spacing, \( v = \dot{x}(t) \) is the velocity of the follower, and \( \Delta v : = \dot{s}(t) \) is the relative velocity between the leader and follower.

One common model used to describe both human driving dynamics and adaptive cruise control vehicle dynamics is an optimal velocity (OV) model [26] with a relative velocity term (OVRV) in the form:

\[ \ddot{x}(t) = \alpha (V(s) - v) + \beta (\Delta v). \quad (4.2) \]

In the above model (4.2), the first component relaxes the follower velocity to a desired velocity prescribed by the optimal velocity function \( V \) based on the current spacing to the vehicle in front, while the second component relaxes the follower velocity to the velocity of the leader. The parameters \( \alpha \) and \( \beta \) control the tradeoffs between following the optimal velocity and following the leader velocity.

For the purposes of modeling adaptive cruise control vehicles, we adopt a special case of the OVRV model (4.2) considered in [104, 105, 106]:

\[ \ddot{x} = f(s, v, \Delta v) = k_1 (s - \tau v) + k_2 (\Delta v) \quad (4.3) \]

where \( k_1 \) and \( k_2 \) are the gain parameters on the constant time-headway term and a follow-the-leader term respectively, and the parameter \( \tau \) is the desired headway. Note that the model (4.3) operates under a linear optimal velocity function \( V(s) := s/\tau \) and with \( \alpha : = k_1 \tau \). It is considered a constant time-headway term because the spacing \( s \) is adjusted based on the speed such that the headway \( \tau \) is maintained. It is well known that constant time-headway based controllers are important to overcome the inherent limitations of linear controllers to achieve a string stable constant spacing policy [107]. The model (4.3) is selected based on the reported
goodness of fit to simulate real trajectories of ACC equipped vehicles in [104, 106].

### 4.3.2 Stability Analysis

In this section the string stability of ACC enabled vehicles in following mode is examined. In broad terms, string stable driving behavior is critical to attenuate disturbances and prevent phantom jams [1] from appearing from initially smooth and uniform flow. A string stable platoon when a leading vehicle experiences a change in velocity will experience a decreasing magnitude of response to the disturbance in vehicles further back in the platoon, as opposed to a string unstable platoon which will experience a response growing in magnitude going back in the platoon.

In Figure 4.1, we determine the stability of (4.3) for ranges of $k_1$, $k_2$ for several different headway settings $\tau$. A result of this analysis is that it becomes clear that for vehicles with less powerful responses, i.e., small $k_1$, $k_2$, a larger desired headway is necessary for string stability. However, a consequence of higher headways is that the traffic stream will have a lower throughput, since density is inversely related to headway.

An illustration of string stability vs. instability is provided in the form of a simulation where 10 vehicles form a platoon. All vehicles follow using the dynamical model in (4.3), except for the lead vehicle. The lead vehicle drives at a constant speed then experiences a step-function decrease in speed, and then after some time a following step-function increase back to the original speed. In Figure 4.2, each vehicle is simulated using (4.3) with values of $k_1 = 0.5$ and $k_2 = 0.5$, with the left simulation using a value of $\tau = 0.75$ seconds and the right using a value of $\tau = 3.0$ seconds. It is easy to verify that for $k_1 = 0.5$ and $k_2 = 0.5$ the two $\tau$ values represent respectively a string unstable system (left), and a string stable system (right). The left simulation displays significant overshoot both on the braking event and the acceleration event. The right simulation shows for the higher $\tau$ that the platoon does not overshoot either the braking or acceleration event and each following vehicle has a smoother response than the preceding vehicle.
Figure 4.1: Necessary $\tau$ of the dynamical model ranging across different $k_1$ and $k_2$ values. A system contained within the white portion of each graph is string stable, while a system in the grey portion is string unstable.

Figure 4.2: Affect of varying $\tau$ on platoon string stability. 9 vehicles in ACC all at $k_1 = 0.5$ and $k_2 = 0.5$ experience a braking and acceleration event under two different $\tau$ values. On the left, $\tau = 0.75$ s while on the right $\tau = 3.2$ s. The left figure shows a string unstable ACC platoon, and the right figure shows a stable platoon.
4.4 Experimental overview and test vehicles

In this section we present the design and execution of a series of field experiments. The goal of the experiments is to observe the vehicle following dynamics of the seven ACC-equipped vehicles tested. Each experiment involves a lead vehicle that executes a pre-determined velocity profile and a following vehicle that follows the lead vehicle under adaptive cruise control.

The ACC system in all commercially-available vehicle tested in this experiment has two input settings: desired speed and desired following setting (ranging from a minimum setting to a maximum setting). The desired speed is set by the driver, and can be specified to the nearest mile per hour.

Each vehicle is equipped with a *U-blox EVK-M8T* GPS evaluation kit that is capable of tracking the position and speed of each vehicle throughout the experiment at a frequency of up to 10 Hz. Each evaluation kit is connected to a *Raspberry Pi* computer, which runs a script to log the data as it is recorded. While GPS is prone to small errors in position, these are often due to atmospheric conditions and are generally correlated for different GPS receivers in the same proximity [108].

4.4.1 Vehicle fleet

The vehicles tested in this experiment are all commonly-available, 2018 model year vehicles obtained from a major rental car agency. The specifics of the vehicles tested are as follows:

- **Vehicle A** - Compact sedan, Manufacturer 1
- **Vehicle B** - Full size sedan, Manufacturer 1
- **Vehicle C** - Hybrid sedan, Manufacturer 1
- **Vehicle D** - Crossover SUV, Manufacturer 1
- **Vehicle E** - Crossover SUV, Manufacturer 2
• **Vehicle F** - Midsize SUV, Manufacturer 2

• **Vehicle G** - Full size SUV, Manufacturer 2

### 4.4.2 Two-vehicle tests

The two vehicle tests were conducted on a 10.1 mile frontage road alongside interstate I-10 north of Tucson, AZ. High speed tests were conducted on the parallel running portion of I-10 between Exit 226 and Exit 236. The posted speed limit on the frontage road was 55 mph and the posted speed limit on I-10 was 75 mph.

Testing of each vehicle consisted of four laps from the starting point to the end point of the test road segment, and back. Three laps were conducted on the frontage road, while one lap was conducted on I-10 for each vehicle. Each lap tested a specific speed profile as described below, and tested two different ACC following settings (one setting for each direction of the lap).

A total of four speed profiles were tested for to observe the behavior of each vehicle in the two-vehicle tests. For all tests, the vehicles begin on the track and start at a low speed with a 2018 Toyota Camry LE as the lead vehicles, and the subject vehicle as the following vehicle. In each test, the specified lead vehicle speed was implemented by setting the lead vehicle’s cruise control to the desired speed. When changing speed, the manual input button was used to adjust the cruise control set point speed of the lead vehicle to the desired speed. This allowed for control of the transition rate between set point speeds. The speed profiles were as follows:

- **Low speed steps:** Vehicles begin at 35 mph and maintain this speed for 60 seconds at which point the speed is increased to 40 mph and held for 60 seconds. Next, the speed is increased to 45 mph, which is held for 60 seconds, and then increased to 50 mph and held for 60 seconds. Finally, the speed is increased to 55 mph, which is held for 60 seconds. The same speeds are next tested in reverse order (50 mph, 45 mph, 40 mph, 35 mph), with each being held for 60 seconds.
• **High speed steps**: Vehicles begin at 65 mph, which is held for at least 60 seconds, then increased to 70 mph, which is held for 60 seconds, and finally increased to 75 mph and held for at least 60 seconds. Next the same speeds are tested in a decreasing order (70 mph and 65 mph) with each held for at least 60 seconds.

• **Speed dips**: Both vehicles begin at 55 mph and hold that speed for at least 45 seconds. For this test, four different speed dips are tested: 6 mph, 10 mph, 15 mph, and 20 mph. Each speed dip is held for 5 seconds before returning to 55 mph for at least 45 seconds. Each speed dip is conducted twice before proceeding to the next speed dip. Additional speed dips are conducted once each speed dip as been conducted at least twice, as space permits at the test site.

• **Oscillatory**: For this test, both 6 mph and 10 mph speed fluctuations are tested. For the first half of the test the speed is fluctuated between 55 mph and 49 mph, with each speed being held for at least 30 seconds. For the second half of the test the speed is fluctuated between 55 mph and 45 mph with each speed being held for at least 30 seconds.

Plots of the collected data for Vehicle B at the minimum following setting are presented in Figure 4.3, and the data for the remaining tests is presented in Figure B.1 through Figure B.13.

### 4.4.3 Platoon tests

Platoon tests were conducted on a 6 mile section of N. Anway Rd. west of Tucson, AZ. The posted speed limit on N. Anway Rd. was 50 mph. All vehicles except for the lead vehicle were of type Vehicle B. The lead vehicle was the University of Arizona Cognitive and Autonomous Test (CAT) Vehicle, a 2008 Ford Escape Hybrid with autonomous capabilities.
Figure 4.3: Two-vehicle test data for Vehicle B with following setting 1.
For the platoon tests, vehicles were arranged in a parking lot on the corner of N. Anway Rd. and W. Manville Rd. When test track was clear of other vehicles, the CAT Vehicle drove on the track followed by the remaining vehicles being tested in a given test. All vehicles began at rest on the track at the beginning of the test. The CAT Vehicle then accelerated to the desired velocity, and the following vehicles manually accelerated to roughly 35 mph before the driver of each vehicle engaged ACC and set the speed for the desired set point speed (55 mph in all tests) and following setting (minimum or maximum depending on the test). The platoon of vehicles was followed by a safety chase vehicle that kept a larger spacing than the vehicles in the test and was intended to act as a buffer to non-experimental traffic and to monitor the safety of the experiment.

During each test, the driver of each vehicle was able to receive basic safety messages from the experiment crew via a two-way radio placed in their vehicle. However, for safety reasons drivers were not permitted to transmit messages while driving the vehicle, and thus were only able to receive information through the two-way radio, and not able to send information. The two-way radio was used for the driver coordinator in the safety chase vehicle to communicate both with the driver of the CAT Vehicle to provide information on when to change the set point velocity as well as to give drivers sufficient warning of changes in the set point speed of the lead vehicle.

As the platoon of vehicles reached the end of the test track, the driver coordinator in the safety chase vehicle communicated with the operators of the CAT Vehicle to end the test and safely come to a stop at a parking lot at the end of the test track. The driver coordinator would also give similar instructions to the drivers of the following vehicles.

The following platoon tests were conducted, with the following speed profiles. For all tests where ACC is engaged all following vehicles have the speed set point set to 55 mph. The following setting is varied by test as indicated below. Tests were conducted in the order listed below.
• **Test 1:** All vehicles are under human control. The lead vehicle drives at roughly 50 mph and all vehicles follow. The data is shown in Figure B.14.

• **Test 2:** All vehicles are under human speed control. The lead vehicle drives at roughly 50 mph. The data is shown in Figure B.15.

• **Test 3:** Platoon of CAT Vehicle followed by 5 vehicles. The lead vehicle manually drives at roughly 50 mph with the five following vehicles using ACC to follow with the maximum following setting. The data is shown in Figure B.16.

• **Test 4:** Platoon test with CAT Vehicle followed by 5 vehicles. The lead manually drives at 50 mph and reduces speed to 40 mph after some time. All vehicles drive with ACC engaged at the maximum following setting. This speed is maintained until the end of the test at which point the lead vehicle slowly reduces speed to 15 mph such that the following vehicles disengage ACC. The data is shown in Figure B.17.

• **Test 5:** CAT Vehicle followed by three vehicles with the maximum following setting. The CAT Vehicle begins at 50 mph and after some time automatically reduces speed to 44 mph, which is held for some time. Toward the end of the test, the CAT Vehicle is switched to manual driving and manual speed fluctuations are conducted by the lead vehicle.

• **Test 6:** CAT Vehicle followed by five following vehicles. The lead vehicle begins at 50 mph and automatically reduces speed to 44 mph after some time, which is held for roughly 1 minute before resuming driving at 50 mph. Each vehicle has the maximum following.

• **Test 7:** CAT Vehicle followed by 5 vehicles. Each vehicle uses the maximum following setting. The lead vehicle starts at 50 mph and once vehicles seem to have reached equilibrium flow, the lead vehicle automatically slows to 40 mph. This is held for some while before a speed of 50 mph is resumed. The data is shown in Figure B.18.
• **Test 8:** CAT Vehicle followed by 6 vehicles. Each vehicle uses ACC with the maximum following setting. CAT Vehicle starts at 50 mph. After all vehicles have reached equilibrium the CAT Vehicle automatically reduces speed to 40 mph which is held for some time before the CAT Vehicle resumes 50 mph. The data is shown in Figure B.19.

• **Test 9:** CAT Vehicle followed by 8 vehicles, which all have the maximum following setting. The CAT Vehicle begins at 50 mph and reduces speed to 40 mph before returning to 50 mph. At each speed, the CAT Vehicle waits until the last vehicle in the platoon has held the desired speed for some time before automatically transitioning to the next speed. The data is shown in Figure B.20.

• **Test 10:** The CAT Vehicle is followed by 8 vehicles in this test, all have the maximum following setting. The CAT Vehicle begins at 50 mph and a 10 mph speed reduction is executed by the CAT Vehicle. The lower speed of 40 mph is held for roughly 1 minute before automatically returning to 50 mph. The data is shown in Figure B.21.

• **Test 11:** CAT Vehicle followed by four vehicles, all use the minimum following setting. The CAT Vehicle begins at 50 mph which is automatically reduced to 44 mph once equilibrium of the platoon is reached. The 44 mph is held for some time before automatically returning to 50 mph. The data is shown in Figure B.22.

• **Test 12:** CAT Vehicle followed by 5 vehicles. All following vehicles have the minimum following setting. In this test, the lead vehicle begins at 50 mph and does not change speed for the duration of this test. The data is shown in Figure B.23.

• **Test 13:** CAT Vehicle followed by 7 vehicles, which all use the minimum following setting. The CAT Vehicle begins at 50 mph and automatically reduces
speed to 44 mph, which is held for some time before automatically returning to 50 mph. Note that in this test, Vehicle 2 (the last vehicle in the platoon) has ACC disengage. The data is shown in Figure 4.5.

In each test, the vehicles are arranged with the lead vehicle in front under human control, while the following vehicle operates under control of the ACC system.

4.5 Model calibration methodology

In order to calibrate the model (4.3), three parameters must be estimated: $k_1$, $k_2$, and $\tau$. The gain parameter $k_1$ corresponds to the strength of response the vehicle experiences with respect to its current error in headway compared to the desired headway, $\tau$. When that headway error is positive (the headway is larger than desired), the vehicle will accelerate to obtain that headway. Gain parameter $k_2$ corresponds to the extent to which the following ACC vehicle will accelerate to match the leading vehicles speed. When the follower is driving at a higher speed than the leader it will decelerate, and when at a lower speed it will accelerate. The parameter $\tau$ must also be estimated like $k_1$ and $k_2$. Unlike $k_1$ and $k_2$ however, $\tau$ is has a direct physical interpretation, namely the headway of the follower under equilibrium flow conditions.

The calibration of the model can be posed as a simulation-based optimization problem in which an error functional is minimized by selecting optimal model parameters. In Milanés and Shladover [103] an absolute valued error metric is proposed that compares the velocity of the ACC model under a given set of parameters to the velocity recorded by the real ACC equipped vehicle. Then, parameters are found to minimize the velocity error.

In this work we instead consider an error metric based on the headway differences between the measured ACC data and a forward simulation of (4.3) under a given parameter set. This choice is made because it substantially reduced the error on the headway and spacing, while also providing small velocity errors. The specific error
The metric used is a headway mean absolute error (MAE):

$$MAE = \frac{1}{N} \sum_{i=1}^{N} |h_{\text{sim}}(i) - h_{\text{meas}}(i)|,$$  \hspace{1cm} (4.4)

where $h_{\text{sim}}(i) := \frac{s_{\text{sim}}(i)}{v_{\text{sim}}(i)}$ refers to the $i^{th}$ simulated headway, $h_{\text{meas}}(i) := \frac{v_{\text{meas}}(i)}{s_{\text{meas}}(i)}$ is the $i^{th}$ measured headway, and $N$ is the number of samples in the dataset/steps in the simulation. $h_{\text{sim}}(i)$ and $h_{\text{meas}}(i)$ both refer to headways which in general are distinct from $\tau$, a parameter in the car following model corresponding to the equilibrium headway.

The calibration of the dynamical model is solved as a simulation-based optimization problem. The values $k_1$, $k_2$, and $\tau$ are found using an unconstrained quasi-Newton search method as implemented in the \texttt{fminunc} function in Matlab. The simulation of the follower vehicle trajectory at each step of the optimization routine is performed via numerical integration using an explicit forward Euler scheme. Because the resulting optimization problem is nonlinear and to account for potential local minima, the optimization routine is run many times using randomly initialized parameters. The parameter value set that yields the lowest MAE is selected as the best fitting parameters. The results of this approach is presented in the next section.

4.6 Results

In this section we first provide an analysis of the accuracy of the GPS units that are used to measure vehicle positions and speeds. Next the calibration of the dynamical model outlined in (4.3) is presented, and the results are compared to the measured ACC data. Using this calibrated dynamical model its string stability is analyzed by using the criteria proposed in (2.19). Finally, simulation results are presented that demonstrate that under different headway settings, while keeping the gains fixed, it may be possible to stabilize a platoon of ACC equipped vehicles (at the cost of capacity).
4.6.1 Validation of GPS measurements

The U-blox evaluation kits are tested for accuracy in speed and position by placing two U-blox sensors a known distance apart on the same vehicle and extensively driving this vehicle to observe the GPS measured distance and difference in speed throughout the drive.

The distance between the two antennae mounted on the same vehicle is computed using the Haversine formula. The mean recorded sensor distance is 1.37 m while the actual sensor distance was 0.94 m. This represents a mean position accuracy accuracy of 0.43 m (Figure 4.4), which corresponds to roughly 1% error when compared to a typical following distance of roughly 45 m following distance at 31 m/s (70 mph). It is worth noting that the largest observed GPS position errors are observed in the urban areas which are far from the rural area used for data collection in the car following tests.

The mean absolute difference in speed between the two sensors is 0.06 m/s (0.13 mph), which is an error of less than 0.2% of the average speeds observed in the tests. The distribution of difference in GPS speed is seen in Figure 4.4.

Due to the overall good agreement between sensor speed and position measurements, the U-blox EVK-M8T is a suitable GPS unit for recording velocity and position data.

4.6.2 Model calibration, validation, and stability

In this section, we calibrate the dynamical model (4.3) to the experimental data collected in the high and low speed step function tests. After applying the calibration algorithm to the oscillatory data, the best fit parameters are presented in Table 4.1.

We next check the stability of the calibrated models under the best fitting parameters. Referring to (2.19), it is easy to see that under the learned model parameters the value of $\lambda_2 > 0$ for each vehicle under either setting, which implies the model is string unstable. This is a negative result in the sense that a platoon of ACC equipped
Figure 4.4: Distribution of error in position measurements between two U-blox EVK-M8T receivers mounted on the same vehicle (top) and distribution of instantaneous difference in speed for same sensors (bottom). The mean absolute error in distance between two sensors is 0.43 m and the mean absolute difference in speed measurements is 0.06 m/s indicating that the U-blox EVK-M8T GPS receiver is able to accurately record position and speed data that can be compared across vehicles.

<table>
<thead>
<tr>
<th>Vehicle</th>
<th>Following setting</th>
<th>$k_1$</th>
<th>$k_2$</th>
<th>$\tau$</th>
<th>MAE</th>
<th>$\lambda_2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Vehicle A minimum</td>
<td>0.0535</td>
<td>0.0645</td>
<td>1.44</td>
<td>0.109</td>
<td>5.33</td>
<td></td>
</tr>
<tr>
<td>Vehicle A maximum</td>
<td>0.0353</td>
<td>0.0645</td>
<td>2.78</td>
<td>0.113</td>
<td>0.934</td>
<td></td>
</tr>
<tr>
<td>Vehicle B minimum</td>
<td>0.0704</td>
<td>0.157</td>
<td>1.41</td>
<td>0.0489</td>
<td>3.60</td>
<td></td>
</tr>
<tr>
<td>Vehicle B maximum</td>
<td>0.0169</td>
<td>0.123</td>
<td>2.50</td>
<td>0.0600</td>
<td>2.44</td>
<td></td>
</tr>
<tr>
<td>Vehicle C minimum</td>
<td>0.0379</td>
<td>0.140</td>
<td>1.57</td>
<td>0.0751</td>
<td>5.04</td>
<td></td>
</tr>
<tr>
<td>Vehicle C maximum</td>
<td>0.0225</td>
<td>0.107</td>
<td>2.84</td>
<td>0.0655</td>
<td>1.18</td>
<td></td>
</tr>
<tr>
<td>Vehicle D minimum</td>
<td>0.0512</td>
<td>0.0945</td>
<td>1.49</td>
<td>0.0810</td>
<td>4.77</td>
<td></td>
</tr>
<tr>
<td>Vehicle D maximum</td>
<td>0.0281</td>
<td>0.116</td>
<td>2.71</td>
<td>0.0679</td>
<td>1.04</td>
<td></td>
</tr>
<tr>
<td>Vehicle E minimum</td>
<td>0.0583</td>
<td>0.0958</td>
<td>1.54</td>
<td>0.0539</td>
<td>3.64</td>
<td></td>
</tr>
<tr>
<td>Vehicle E maximum</td>
<td>0.0666</td>
<td>0.0261</td>
<td>2.36</td>
<td>0.0365</td>
<td>0.860</td>
<td></td>
</tr>
<tr>
<td>Vehicle F minimum</td>
<td>0.0848</td>
<td>0.0652</td>
<td>1.42</td>
<td>0.0686</td>
<td>3.39</td>
<td></td>
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<tr>
<td>Vehicle F maximum</td>
<td>0.0447</td>
<td>0.0615</td>
<td>2.25</td>
<td>0.0578</td>
<td>1.46</td>
<td></td>
</tr>
<tr>
<td>Vehicle G minimum</td>
<td>0.0803</td>
<td>0.0657</td>
<td>1.46</td>
<td>0.0647</td>
<td>3.25</td>
<td></td>
</tr>
<tr>
<td>Vehicle G maximum</td>
<td>0.0472</td>
<td>0.0584</td>
<td>2.24</td>
<td>0.0482</td>
<td>1.41</td>
<td></td>
</tr>
</tbody>
</table>

Table 4.1: Calibrated parameters for model (4.3) for each vehicle tested in the experiment.
vehicles operating under the driving conditions used to fit and validate the model can be expected to amplify small perturbations for all vehicles tested, potentially leading to the occurrence of phantom traffic jams. We provide simulation insights regarding the behavior of platoons of ACC vehicles of type Vehicle B operating under these parameters to further investigate the stability of these vehicles.

4.6.3 Implications of ACC dynamics on platoon string stability

In order to interpret the implications of different ACC model parameter values on traffic flow, experiments with up to 8 vehicles of type Vehicle B, and simulations of 10-vehicle of type Vehicle B platoons are performed. In simulation, first a platoon is simulated using the parameters obtained from the calibration procedure in the previous step. Next a platoon is simulated where all vehicles use the same $\tau$ as found to minimize (4.4), but with $k_1$ and $k_2$ sufficiently large to stabilize the model. Finally, the platoon simulation is performed using the original $k_1$ and $k_2$ found to minimize (4.4), but with $\tau$ sufficiently large to stabilize the model. The results indicate that substantial overshoot in speed and headway are observed in unstable platoons, but the model parameters can be modified to eliminate overshoot and stabilize the traffic flow.

As seen in Figure 4.5 where the platoon data collected from Test 13 is presented, the ACC systems of Vehicle B cause a clear amplification of a small disturbance in the speed of the lead vehicle, consistent with unstable systems. This experiment verifies the unstable results expected from the stability analysis conducted on the calibrated model for Vehicle B.

Since the model parameter values that minimize (4.4) are found to be unstable, an area of overall concern is the affect that string instability in these vehicles will have on the broader traffic flow. This is explored by simulating the performance of 9 ACC vehicles in series behind the leading vehicle, which follows the trajectory of the lead vehicle in Test 1. The results are displayed in Figure 4.6, which shows the performance for the calibrated values. In the speed profile the experimentally
Figure 4.5: Platoon data for Test 13 showing amplification of the speed disturbance. The recorded profile is shown in red, while the second vehicle is shown in blue, and the remaining vehicles are plotted with a color gradient from blue to green which corresponds to the placement of the vehicle with respect to the lead vehicle in the platoon. Spacing and headway follow the same color gradient, but do not have a lead vehicle, since the lead vehicle is assumed to drive independent of other vehicles. As seen in Figure 4.6, this scenario corresponds to an unstable platoon, and the following vehicles in speed and headway. In some instances, the overshoot is quite dramatic, with the last vehicle in the platoon experiencing speed swings above and below the leading vehicle of as much as 4.5 m/s (10 mph).

One approach to stabilize the model is to increase the parameter values $k_1$ and $k_2$. Selecting $k_1 = 0.75$, $k_2 = 0.75$, and $\tau = 1.29$ seconds yields a string stable dynamical model. These model values are simulated in a 10-vehicle platoon as described above, and the resulting speed, spacing, and headway profiles of all vehicles in the platoon are presented in Figure 4.7. The result is that the vehicles in the platoon no longer suffers from overshooting in speed, spacing, or headway, and also maintains the desired $\tau$ of 1.29 seconds. While in this scenario the platoon may be string stable, the conditions for stability may be unrealistic, as increases in $k_1$ and $k_2$ correspond
more to the response ability of the vehicle and less to tangible driving behaviors, which means this may not be a truly feasible direction to explore.

As an alternative to increasing the parameter values $k_1$ and $k_2$, the ACC model can also be stabilized by increasing the headway $\tau$. The headway required to achieve stability using the $k_1$ and $k_2$ found by minimizing (4.4) is $\tau = 3.2$ s. The simulation results for the same 10 vehicle platoon setup as before but with $\tau = 3.2$ s are presented in Figure 4.8, where the vehicles are spaced sufficiently far apart to avoid overshoot in speed, spacing, and headway since the model is string stable. While this method for string stability improvement may be realistic in implementation potential it also means that the throughput of traffic stream will be decreased.

4.7 Conclusions

We briefly summarize the main results of this chapter, and discuss their significance. The findings presented in this chapter demonstrate that the string stability of an ACC system depend on the individual vehicle settings. Vehicle-following experiments are conducted with a common, commercially-available sedan that is equipped with an ACC system. The collected data is used to calibrate a constant time headway optimal velocity model for seven commercially-available ACC vehicles. The resulting models are identified to be string unstable. By increasing the desired headway or by increasing gain parameter values in the ACC model are both able to stabilize the system for the one vehicle considered in more detail. However, each of these come with limitations since increased headway reduces the capacity of the roadway while increased gain values may not be feasible for implementation on an actual vehicle.

This chapter is a preliminary study that addresses the question of string stability of seven different commercially-available ACC vehicles. However, it is limited in that it only considers a range of speeds. Furthermore, the impact of speed setpoint on car following behavior are not tested.
Figure 4.6: Ten vehicle platoon simulated with unstable parameter values $k_1 = 0.045$, $k_2 = 0.30$, and $\tau = 1.29$ for an experimentally-collected lead vehicle profile.
Figure 4.7: Ten vehicle platoon simulated with stable parameters $k_1 = 0.75$, $k_2 = 0.75$, and $\tau = 1.29$ for an experimentally-collected lead vehicle profile.
Figure 4.8: Ten vehicle platoon simulated with stable parameters $k_1 = 0.045$, $k_2 = 0.30$, and $\tau = 3.20$ for an experimentally-collected lead vehicle profile.
Based on the analysis presented in this chapter, it is clear that the limitations of commercially-available ACC systems that were identified in Bareket et al. [102] and in Milanés and Shladover in 2014 [103] may still be true today.
Chapter 5

Traffic control with CAVs

5.1 Introduction

The primary contribution of this dissertation is the demonstration that a small number of AVs are capable of dampening phantom traffic jams and stabilizing the traffic flow, even before the majority of vehicles in the flow have autonomous capabilities. This result is significant, since it means that if vehicle controllers are properly designed, we may see substantial improvements in traffic stability, throughput, and fuel consumption before the entire vehicle fleet is automated.

This chapter presents results that demonstrate three possible controllers that are able to achieve substantially improved traffic conditions by controlling the vehicle speed of a single AV on a track of up to 21 human-piloted vehicles. These results build on the experiments presented in Chapter 3 and present results for AVs that are more advanced than the longitudinal controllers tested in Chapter 4. Many of the results presented in this chapter are also published in [13].

5.1.1 Motivation

As introduced in Chapter 2, the dynamics of traffic flow include instabilities as density increases, where small perturbations amplify and grow into stop-and-go waves
that travel backwards along the road [1, 109, 110, 111]. These so-called phantom traffic jams are an experimentally reproducible phenomenon, as demonstrated in different experiments [1, 8, 11, 12]. Common wave triggers include lane changing [112, 113, 114], but they can even be generated in the absence of any lane changes, bottlenecks, merges, or changes in grade [1, 8]. Moreover, these waves can be captured in microscopic models of individual vehicle motion [26, 115, 116] (see also the reviews [7, 117, 118]) and macroscopic models described via solutions to continuum problems [110, 119, 120, 121, 122, 123]. Since these waves emerge from the collective dynamics of the drivers on the road, they are in principle avoidable if one could affect the way people drive. Recognizing the rapid technological innovations in traffic state estimation and control, this work provides experimental evidence that these waves can be reduced by controlling a small number of vehicles in the traffic stream.

A necessary precursor to dissipating traffic waves is to detect them in real-time. Advancements in traffic state estimation [124, 125, 126] have facilitated high resolution traffic monitoring, through the advent of GPS smartphone sensors [127, 128, 129, 130] that are part of the flow—termed Lagrangian or mobile sensors. Now commercialized by several major navigation services, the use of a small number of GPS equipped vehicles in the traffic stream has dramatically changed how traffic is monitored for consumer-facing mobility services, which previously relied on predominantly fixed sensing infrastructure.

Currently, traffic control is dominated by control strategies that rely on actuators at fixed locations or are centralized. Such systems include variable speed advisory (VSA) or variable speed limits (VSL) [131, 132, 133, 134, 135], which are commonly implemented through signs on overhead gantries, and ramp metering [136, 137, 138], which relies on traffic signals on freeway entrance ramps. More recently, coordinated systems to integrate both ramp metering and variable speed limits have been proposed [139, 140, 141, 142]. A common challenge of VSL and ramp metering systems is the small flexibility of the systems due to the high cost of installation of the fixed infrastructure, which consequently limits the spatial resolution of the control input.
Additionally, compliance with the speed advisory is not guaranteed, which can limit the effectiveness of the control strategy.

Recent advancements in vehicular automation and communication technologies have the potential to substantially change surface transportation [5, 143, 144, 145, 146]. In particular, these advancements provide new possibilities and opportunities for traffic control in which these smart vehicles act as Lagrangian actuators of the bulk traffic stream. When a series of adjacent vehicles on a roadway are connected and automated, it is possible to form dense platoons of vehicles which leave very small gaps. A key challenge for vehicle platoons is to design control laws in which the vehicle platoon remains stable, for which significant theoretical and practical progress has been made [15, 84, 85, 86, 87, 88, 89, 90, 91]. Recent work has shown that commercially-implemented, string-stable adaptive cruise control (ACC) systems may result in an unstable traffic state when implemented on a platoon of ACC-enabled vehicles, motivating the need for vehicle connectivity in such systems [103, 106]. In contrast to the vehicle platoon setting, in which all vehicles are controlled, or the variable speed limit and ramp metering strategies which actuate the flow at fixed locations, this research aims to dissipate congestion-based stop-and-go traffic waves using only a sparse number of autonomous vehicles already in the flow, without changing how the other, human-driven, vehicles operate.

The notion to dissipate stop-and-go waves via controlling vehicles in the stream represents a shift from stationary to Lagrangian control, mirroring the transition to Lagrangian sensing that has already occurred. The key advantage in mobile sensing projects [127, 129, 130] is that a very small number of vehicles being measured (3-5%) suffices to estimate the traffic state on large road networks [128]. In the same spirit, our research experimentally demonstrates that a small number of Lagrangian controllers suffices to dampen traffic waves.

The ability of connected and automated vehicles to change the properties of the bulk traffic flow is already recognized in the transportation engineering community. For example, the works [80, 81, 82, 83, 147] directly address the setting where a
subset of the vehicles are equipped with automated and/or connected technologies, and then assess via a stability analysis or simulation the extent to which the total vehicular flow can be smoothed. Recently, several works have explored extensions to the variable speed limit control strategies in which connected or automated vehicles are used to actuate the traffic flow [148]. For example, the work by [149] develops a VSL strategy that is implemented in simulation with connected vehicles where the traffic evolves according to the kinematic wave theory. It follows a similar strategy proposed by [150], where a coordinated VSL and ramp metering strategy is implemented via actuation of the entire vehicle fleet (i.e., 100% penetration rate). Although not explicitly designed as a variable speed limit controller, [151] advocates a “slow-in, fast-out” driving strategy to eliminate traffic jams, using a microscopic model also in line with kinematic wave theory. The work by [152] proposes a similar jam absorbing strategy as [151] based on Newell’s car following theory, and its effectiveness is assessed in simulation.

Interestingly, an experimental test of the “slow-in, fast-out” strategy [151] is provided by [153], in which five vehicles are driven on a closed course. The lead vehicle in the platoon of five vehicles drives initially at a constant speed, then decelerates as if driving through a congestion wave, and then accelerates back to the cruising speed. The third vehicle in the platoon initially leaves a large gap, and due to the extra gap it is able to maintain the cruising speed and effectively absorb the jam. In contrast to the experiment by [153], the present work fully replicates the setup of [1] and [8], in which the stop-and-go wave is generated naturally from the human drivers in the experiment, without an external cause. Moreover, the controllers proposed in the present work are distinct.

We also note some preliminary field experiments to harmonize speeds via connected vehicles are recently reported by [154] and [155], in part to measure the impact of connected vehicles following an infrastructure-generated advisory speed on the traffic stream behind the connected vehicles. In the present chapter, we instead dampen waves on a closed ring, which simplifies the experimental setup, and
facilitates detailed data collection on the performance of the controllers.

5.1.2 Problem statement and contributions

The present chapter is inspired by the work of [1] and [8] which are the first works to demonstrate via experiments that traffic waves can emerge as a result of human driving behavior alone. A series of experiments is conducted where approximately 20 vehicles drive in a ring of fixed radius with each driver following the vehicle in front of them. The experiments of [1] and [8] are foundational because they demonstrate the emergence of traffic waves caused (unintentionally) by human driving behavior. However, they do not offer a solution for dampening these waves.

To address this gap, we design and execute a series of ring-road experiments which show that an intelligently controlled autonomous vehicle is able to dampen human-generated stop-and-go waves. The experimental setup (described in Section 5.2) follows the setting of of [1] and [8], with the modification that one vehicle is an autonomous-capable vehicle which can run a variety of longitudinal control laws. Similar to the [1] experiment, the position and velocity of each vehicle is tracked via a 360 degree camera. We additionally instrument each vehicle in the 22-car fleet with an OBD-II scanner to log the real-time fuel consumption of each vehicle, such that the impact of the traffic waves and controllers on the bulk fuel consumption can be recorded.

The experimental setup used allows for us to isolate the effect traffic instabilities caused by human car following behavior, while eliminating other sources of congestion. Specifically, this work does not aim to quantify the effect of AVs on congestion triggers such as lane changing or geometric bottlenecks such as a reduction in lanes. Instead, the experimental setup is designed to easily study traffic waves caused by the car-following behavior of human drivers, and consequently follows a similar experimental design used in [1]. It is important to stress that the ring setup does not represent all of the complexities of human driving behavior on long stretches of roadway. However it does allow the emergent phenomenon of stop-and-go waves,
which are observed in freeway traffic flows, to be reliably reproduced so that the effectiveness of AV control laws designed to dampen these waves can be quantified. These experiments should be viewed as a precursor to larger field experiments on real freeways.

We present three experiments (labeled as A, B, and C in Section 5.4) and two distinct control strategies (detailed in Section 5.3) that can be used to dampen stop-and-go waves created by human drivers. The first control strategy is to follow a fixed average velocity (selected based on observation) as closely as possible without collisions. It is implemented in Experiment I via an automatic control algorithm (called *FollowerStopper*) and in Experiment J via a carefully trained human driver. The second type of control strategy is a *proportional-integral (PI) controller with saturation*, which is a natural extension of the PI controller, a simple and widely used controller in industrial applications. The controller is only based on the knowledge of the autonomous vehicle speed over a time horizon. The control action is saturated at small gaps to avoid collisions, and long gaps to avoid slowing down of traffic. Compared to the average velocity controllers (Experiments I and J), the PI controller with saturation directly estimates the average velocity and thus needs no external input.

5.2 Experimental methodology

We briefly describe the experimental setting in which stop-and-go waves are observed to develop and subsequently dampened via control of a single vehicle in the experiment (mimicking a uniform low penetration rate on a long freeway stretch). The experiments follow the ring setting of [1] and [8]. A key advantage of the ring road experimental setup [1, 8] is that it removes other effects like boundary conditions, merging lanes, or intersections. To aid in interpretation of trajectory and fuel consumption datasets made available with this work, we concisely describe the experimental design and data collection methods in Section 5.2.1. The proto-
col for each experiment, including the specific instructions given to the drivers are presented in Section 5.2.2.

5.2.1 Experiment design

The experimental design used in this experiment is the same as the designed presented in Chapter 3. To summarize, we consider a single-lane circular track of radius 41.4 meters to the center of the lane (260 meter circumference) with 21 to 22 vehicles depending on the experiment. Small modifications to the of [1] and [8] setup include a larger circumference of the circle and driving in counter-clockwise direction, to account for the larger average US vehicle size and the location of the steering wheel. An asphalt track is marked with small circular cones, and is otherwise nearly flat and uniform (no marking, light poles, parking barriers, or other potential obstacles). Short (3 cm) orange indicators are placed to mark the inside of the track ring.

A fleet of 22 passenger vehicles equipped with data acquisition hardware is used in the experiment. One of the 22 vehicles is the University of Arizona CAT Vehicle, which can be transitioned between manual velocity control and autonomous velocity control. A trained human driver controls the steering wheel of the CAT Vehicle at all times during all experiments. We underscore that only one vehicle is ever controlled to dampen the traffic wave, either via automation of the vehicle velocity or through the trained driver. This setting in which a single vehicle is controlled on a ring road approximates a low penetration rate of connected and automated vehicles on a long stretch of highway with AVs uniformly spaced in the traffic. The connectivity allows the AVs to receive non-local information about the presence of a wave. This enables the control to have a larger affect on the wave when the AV reaches the wave. All other vehicles are driven by University of Arizona employees that have completed safe driver training but received no other special driving training. Drivers are instructed to drive safely and are requested to attempt to close any widening gaps between their vehicle and the vehicle ahead (see Section 5.2.2 for the precise driver instructions).
Data from each experiment is collected via a video camera and OBD-II data loggers. The 360 degree camera is placed at the center of the track and used to record each experiment. The resulting video is processed via computer vision techniques to identify the center of each vehicle in each frame, which is then smoothed to generate the vehicle trajectories, following the approach described in [9] and in Chapter 3. Data from the in-vehicle devices are gathered through the OBD-II standard interfaces available on all US cars starting in 1996 [156]. The in-vehicle devices measure the instantaneous fuel consumption of each vehicle.

5.2.2 Experiment mechanics

The experiment mechanics used for these experiment is similar to the mechanics presented in Chapter 3. However, they are distinct in that in this chapter, the CAT Vehicle is driven autonomously. Each experiment lasts between 7–10 minutes to limit driver fatigue and begins with all vehicles uniformly spaced around the track according to the position of their front-left tire. The CAT Vehicle begins each experiment in manual mode, and is switched into a control mode during the experiment. Traffic waves appear in all experiments, and the unsteady traffic is allowed to persist for at least 45 seconds before a controller is activated. For some controllers, a desired average velocity is communicated from an external observer.

Precisely, each experiment consists of the following phases: (i) setup; (ii) evacuation; (iii) initialize; (iv) drive; (v) stop; and (vi) conclusion, summarized below.

i. Setup: Vehicles are distributed equally according to the spacing of their front-left tire. Drivers are individually instructed to turn on their in-vehicle data recorders. Additional driver instructions (if any) are delivered to individual drivers through the window.

ii. Evacuation: The central camera is switched on. All research team personnel evacuate the track.
iii. Initialize: An air horn sounds to instruct all drivers to switch gears from Park to Drive, without moving.

iv. Drive: An air horn sounds, to instruct all drivers to begin driving.

v. Stop: An air horn sounds, instructing drivers to come to a safe stop and switch gears into Park.

vi. Conclusion: Experiment personnel enter the track after all vehicles have stopped. Drivers are individually instructed to turn off their in-vehicle recorders. The central camera is switched off.

The following instructions are provided to each driver prior to the start of the experiments. “Drive as if you were in rush hour traffic. Follow the vehicle ahead without falling behind. Do not pass the car ahead. Do not hit the car ahead. Drive safely at all times. Do not tailgate. But put an emphasis on catching up to the vehicle ahead, if a gap starts opening up.” The purpose of these instructions is to explicitly prevent the human drivers from intentionally smoothing out traffic waves themselves. This is important, so that the wave-smoothing effect solely caused by the CAT Vehicle can be studied.

In the event of an unsafe scenario, the drivers are instructed to steer out of the circle, at which the experiment coordinator will sound the air horn and the experiment will stop. All drivers are instructed that the CAT Vehicle would be switching back and forth between autonomous and manual mode, and that they should focus on their driving rather than attempting to guess what mode the vehicle is in at any given time. The vehicle directly following the CAT Vehicle is told to drive as if the CAT Vehicle were in the same lane, and that the CAT Vehicle will be driving at a larger radius (1/2 vehicle width) to facilitate evasive emergency maneuvers.
5.3 Description of controllers of the autonomous vehicle

This section presents the velocity controllers implemented on the CAT Vehicle, which are observed to dampen traffic waves on the ring track. The controllers are broadly motivated by the fact that mathematical models of vehicular traffic can be stabilized via the control of a small number of vehicles, see for example [28, 80, 81, 82, 83]. The main goal when stabilizing the traffic flow is to control the traffic such that all vehicles drive at the same constant velocity, without slowing down or speeding up. One method that can help stabilize the overall flow is to have a subset of vehicles drive with a smooth driving profile relative to the traffic conditions, which is the basis of the works by [150], [151], and [152].

For the ring setup containing many human-piloted vehicles and a single AV, flow stabilization can be achieved when the AV has a control strategy that promotes it to drive at the equilibrium speed [28]. Mathematically the effectiveness of the controller is established via a linear stability analysis that is valid in the neighborhood of the linearization (i.e., near the smooth and uniform equilibrium flow). Consequently the analysis of the controller should be interpreted as stabilizing the flow around the equilibrium, and thus it prevents stop-and-go waves from arising. Moreover, although a single vehicle is used on the ring setup, the result should be interpreted as requiring a penetration rate of AVs that are endowed with communication capabilities on a long stretch of road. Specifically, AVs with connectivity are placed uniformly at 1 every $n$ vehicles, where $n$ is the number of vehicles on the track. If the spacing is not uniform, the penetration rate would likely have to increase.

Despite the origin of the control design as a wave prevention controller, in this work we show a stronger experimental result. Indeed, the control algorithms will be shown to substantially dampen and in some cases completely eliminate stop-and-go waves that are already present in the traffic stream. To understand why a control law designed to prevent waves may also dampen waves that are present, note that the AV is promoted to drive at the equilibrium speed in the stabilizing
controller. When the equilibrium speed (driven by the AV) is close to the average speed (i.e., travel time divided by distance traveled) of traffic ahead of the AV when waves are present, the waves will be dissipated by the stabilizing controller. Precisely, when the equilibrium speed is equal to the average speed of the vehicle ahead traveling through stop-and-go waves, the AV will travel the same distance as the lead vehicle in the same amount of time, but with a constant speed profile rather than an oscillatory one. Consequently, the AV will at times be driving slower than the vehicle ahead of it, thereby opening a gap as the lead vehicle is racing towards the stopped traffic in the wave, and at times faster than the vehicle ahead, closing the gap while the lead vehicle is stopped in the wave. Additional logic is necessary to prevent extremely small gap (unsafe) situations from appearing, or large gaps that may induce lane changing on multi-lane roadways. Again, note that the dampening should be interpreted as occurring due to a penetration rate of AVs, especially in the case when the wave is not eliminated by a single pass of the AV.

With these ideas in mind, we propose two possible control laws and show experimentally that they are able to substantially dampen waves that appear on the ring. The general structure of the controllers is as follows. The CAT Vehicle continuously tracks its velocity $v^{AV}$, and measures (at a sampling rate of 30Hz) the gap $\Delta x$, defined as the distance from its front bumper to the rear bumper of its lead vehicle ahead. This signal, suitably smoothed, is used to calculate the velocity difference $\Delta v = \frac{d}{dt}\Delta x$ between the lead vehicle and the AV. The lead vehicle's (i.e., the car ahead of the AV) velocity is estimated on-board the CAT Vehicle as $v^{lead} = v^{AV} + \Delta v$. Moreover, a desired velocity $U$ is defined (obtained in various ways, see below), which, when chosen correctly, can dissipate waves and stabilize the traffic flow. From the desired velocity, the gap, and the velocities of the CAT Vehicle and lead vehicle, a commanded velocity $v^{cmd}$ is determined. The commanded velocity is then passed to a low-level controller on the CAT Vehicle that translates it into an actuation of the accelerator or brake. Note that all of these quantities are functions of time; but the time argument is frequently omitted for notation.
efficiency. Below, we describe: strategies to define a desired velocity, the *Follower-Stopper* controller and a PI controller with saturation, the low level controls, and a control law implemented by a trained human driver.

### 5.3.1 The FollowerStopper controller

The premise of this controller is to command exactly the desired velocity $U$ whenever safe (i.e., as in a standard cruise controller), but to command a suitable lower velocity $v^{\text{cmd}} < U$ whenever safety requires, possibly based on the lead vehicle’s velocity. Practically, $U$ is the only traffic-dependent parameter in the controller and could be determined in a number of ways. For example, $U$ could be obtained through vehicle connectivity (e.g., AVs ahead in the flow communicate to share average velocity). All other parameters discussed below depend on vehicle dynamics and safe driving requirements.

Using the gap $\Delta x$ and the velocity difference $\Delta v = \frac{d}{dt} \Delta x = v^{\text{lead}} - v^{\text{AV}}$, the $\Delta x - \Delta v$ phase space is divided into regions (see also Figure 5.1):

i. a safe region, where $v^{\text{cmd}} = U$,

ii. a stopping region, where a zero velocity is commanded,

iii. an adaptation region (two parts), where some average of desired and lead vehicle velocity is commanded.

The rationale for providing two adaptation regions is that a common characteristic of driving behavior is to adopt the velocity of the lead vehicle. Thus, in adaptation region I a speed which corresponds to a weighted average between zero velocity and $v^{\text{lead}}$ is commanded, while in adaptation region II the controller commands a speed which corresponds to a weighted average between the lead vehicle velocity and the desired velocity $U$. As a consequence, in adaptation region I $v^{\text{cmd}}$ is independent of the desired control velocity $U$ and only depends on $v^{\text{lead}}$. Specifically, in adaptation region I, the gap is too small to drive at $v^{\text{lead}}$ (if it is smaller than $U$), but large
enough to drive above zero. In adaptation region two, the gap is too small to drive at $U$, but sufficiently large to drive at a speed greater than $v^{\text{lead}}$. At the boundary between adaptation region I and II, $v^{\text{cmd}} = v^{\text{lead}}$.

The boundaries between the regions are parabolas in the $\Delta x - \Delta v$ phase space (trajectories that the AV/lead vehicle pair would traverse when decelerating at constant rates), defined as

$$
\Delta x_k = \Delta x^0_k + \frac{1}{2d_k}(\Delta v_-)^2, \quad \text{for } k = 1, 2, 3.
$$

Here $\Delta x^0_k$ is a parameter that defines the intercept in the $\Delta x - \Delta v$ phase space, $k$ is the curve index, and $d_k$ controls the curvature and is interpreted as a vehicle deceleration rate. Moreover, $\Delta v_- = \min(\Delta v, 0)$ is the negative arm of velocity difference, i.e., the case of the CAT Vehicle falling behind is treated just like the case $v^{AV} = v^{\text{lead}}$.

Using the region boundaries defined in (5.1), the commanded velocity is

$$
v^{\text{cmd}} = \begin{cases} 
0 & \text{if } \Delta x \leq \Delta x_1 \\
\frac{\Delta x - \Delta x_1}{\Delta x_2 - \Delta x_1} & \text{if } \Delta x_1 < \Delta x \leq \Delta x_2 \\
v + (U - v)\frac{\Delta x - \Delta x_2}{\Delta x_3 - \Delta x_2} & \text{if } \Delta x_2 < \Delta x \leq \Delta x_3 \\
U & \text{if } \Delta x_3 < \Delta x.
\end{cases}
$$

Figure 5.1: Regions defined in FollowerStopper controller.
In (5.2), the velocity $v = \min(\max(v^{\text{lead}}, 0), U)$ is the lead vehicle velocity (if positive) or the desired velocity, whichever is smaller. Additionally, $\Delta x_1, \Delta x_2, \Delta x_3$ are the following distances that define the four regions of the controller, and $d_1, d_2, d_3$ are deceleration rates. The parameter $d_1$ is the maximum desirable deceleration rate in the CAT Vehicle and is based on passenger comfort. In the adaptation regions ($\Delta x_1 < \Delta x \leq \Delta x_3$), the commanded velocity transitions continuously from stopping ($v^{\text{cmd}} = 0$, for short gaps) to safe driving ($v^{\text{cmd}} = U$, for large gaps), via a transition involving the lead vehicle’s velocity.

As implemented, in (5.1) and (5.2) we set $\Delta x_1^0 = 4.5 \text{ m}$, $\Delta x_2^0 = 5.25 \text{ m}$, and $\Delta x_3^0 = 6.0 \text{ m}$, and the deceleration rates are $d_1 = 1.5 \frac{\text{m}}{\text{s}^2}$, $d_2 = 1.0 \frac{\text{m}}{\text{s}^2}$, and $d_3 = 0.5 \frac{\text{m}}{\text{s}^2}$. Note that the $\Delta x_k$ boundaries of the regions depend strongly on the velocity difference between the CAT Vehicle and the lead vehicle. For instance, if the CAT Vehicle is catching up rapidly at $\Delta v = -3 \frac{\text{m}}{\text{s}}$, then $\Delta x_1 = 7.5 \text{ m}$, $\Delta x_2 = 9.75 \text{ m}$, and $\Delta x_3 = 15 \text{ m}$. All controller parameters except for $U$ were calibrated through extensive testing with two-vehicles (i.e., follower and leader) before the main experiments.

### 5.3.2 The PI with saturation controller

The idea behind this controller is that the CAT Vehicle may estimate the average speed of the vehicles in front, and then drive according to the average speed. When stop-and-go waves are present, it allows a gap to open up in front of the CAT Vehicle when the lead vehicle accelerates, which is then closed when the lead vehicle decelerates. An estimate of the average speed required by the controller is obtained by measuring the CAT Vehicle speed over a large enough time horizon.

The controller determines a command velocity $v^{\text{cmd}}$ following a standard proportional integral control logic [157], where the deviation from the average speed is treated as the error signal in the PI controller. This simple idea needs to be paired with saturation: for small gaps the CAT Vehicle should follow the lead vehicle speed to avoid dangerous situations, while for large gaps, the CAT Vehicle should catch
up to the lead vehicle.

More precisely, this controller estimates the desired velocity, \( U \), as a temporal average of the CAT Vehicle’s own velocity over an interval. Letting \( v_1^{AV}, \ldots, v_m^{AV} \) denote the CAT Vehicle velocities over the last \( m \) measurements, the desired velocity is computed as the temporal average \( U = \frac{1}{m} \sum_{j=1}^{m} v_j^{AV} \). In practice, we choose \( m \) corresponding to a 38 second interval, which is approximately the time required to travel one lap around the ring. Thus, the CAT Vehicle measures the average speed to circle the ring-road once, and uses this as an estimate for the equilibrium velocity. To obtain an estimate of \( U \) over the first 38 seconds of the experiment, measurements are initialized with zeros. For implementation on a long stretch of roadway (as opposed to the ring), \( U \) would need to be estimated from the flow ahead of the AV in a similar fashion (e.g., using vehicle connectivity) as in the FollowerStopper controller described above.

The desired average velocity is then translated into a target velocity depending on the current gap between the CAT Vehicle and lead vehicle:

\[
v_{\text{target}} = U + v_{\text{catch}} \times \min(\max(\Delta x - g_l, 0), 1), \quad (5.3)
\]

which is up to \( v_{\text{catch}} \) above \( U \), where \( g_l \) is the lower gap limit and \( g_u \) is the upper gap limit. This allows the CAT Vehicle to drive faster than the average velocity and catch up to the lead vehicle, should it face a gap above the lower threshold \( g_l \), while at lower gaps the target velocity reduces to the average \( U \). At gaps above the upper gap limit \( g_u \), the CAT Vehicle should close the gap by traveling \( v_{\text{catch}} \) above \( U \).

The commanded velocity sent to the low level CAT Vehicle controller is updated via the rule

\[
v_{\text{cmd}}^{j+1} = \beta_j (\alpha_j v_{\text{target}}^j + (1 - \alpha_j) v_{\text{lead}}^j) + (1 - \beta_j) v_{\text{cmd}}^j, \quad (5.4)
\]

where the subscript \( j \) denotes the time step. This rule (5.4) chooses the new commanded velocity as a weighted average of the prior commanded velocity, the target
velocity, and the lead vehicle’s velocity. The weights \( \alpha_j \) and \( \beta_j \) depend on the gap as follows: 
\[
\beta_j = 1 - \frac{1}{2} \alpha_j, \\
\alpha_j = \min(\max\left(\frac{\Delta x - \Delta x^*}{\gamma}, 0\right), 1).
\] (5.5)

In (5.5), the distance \( \Delta x^* \) is a safety distance. We have \( \alpha_j = 0 \) if \( \Delta x \leq \Delta x^* \) and \( \alpha_j = 1 \) if \( \Delta x \geq \Delta x^* + \gamma \), meaning that for relatively short gaps, only the lead vehicle’s velocity matters, while for relatively large gaps, only the target velocity is averaged with the commanded velocity. The parameter \( \gamma \) controls the rate at which \( \alpha \) transitions from 0 to 1, and is set to \( \gamma = 2 \) m in the current implementation. This means that when the gap is short, the CAT Vehicle has the same speed of the lead vehicle, while when the gap is larger the CAT Vehicle speed tends towards the target vehicle, which allows the CAT Vehicle to reduce the gap with the lead vehicle.

The parameter \( \beta_j \) determines how rapidly the controller adjusts to new situations (with more rapid adjustments occurring in more safety-critical situations). At its core, this is a PI controller, but with a saturation at small gaps (for safety purposes), and a saturation at large gaps (so that the CAT Vehicle closes gaps).

The model parameters for both controllers were determined via testing in a simulation environment (with a data-fitted human-driver model), as well as via car-following field tests with two vehicles (before the actual experiments). The human-driver model used for simulation is the optimal velocity-follow the leader (OV-FTL) model calibrated to match the macroscopic properties of the traffic observed in the experiment of of [1], for details see [28]. As a result we set the lower gap limit \( g_l = 7 \) m, the upper gap limit as \( g_u = 30 \) m and \( v^{\text{catch}} = 1 \) m/s. The safety distance is implemented as \( \Delta x^* = \max(2 s \times \Delta v, 4 \) m). The term \( 2 s \times \Delta v \) represents the recommended safe following headway of 2 s, with a lower bound of 4 m.
5.3.3 Low level vehicle controls

The commanded velocity produced by the two controllers described above is trans-
lated to the actual vehicle controls (i.e., gas and brake signals) via a multi-mode
controller. The use of a multi-mode controller permits different gains to be used
for acceleration or for braking, to enable faster braking when needed while avoiding
chattering at steady-state velocities.

Each mode is a PID controller, with gains determined through system identifi-
cation of the CAT Vehicle at constant velocities representative of those recorded in
the experiment, using a similar structure as in [158]. The CAT Vehicle plant is sim-
plified as a first-order model based on constant accelerator inputs. The controller’s
design is thus:

\[
a_{j+1} = \begin{cases} 
  h_1(v_j, v^\text{cmd}_j) & \text{if } v^\text{cmd}_j - v_j > -0.25 \text{ m/s} \\
  h_2(v_j, v^\text{cmd}_j) & \text{if } v^\text{cmd}_j - v_j \leq -0.25 \text{ m/s} \\
  0 & \text{otherwise} 
\end{cases}
\]

in which \(a_{j+1} \in [-100, 100]\) represents the next commanded “acceleration” value,
where 100 is the maximum depression of the accelerator, and -100 is the maximum
depression of the brake. Moreover, \(v_j\) is the current speed of the CAT Vehicle,
and \(v^\text{cmd}_j\) is the desired speed. When \(a < 0\) the brake is depressed, and when
\(a > 0\) the accelerator is depressed. Controller \(h_1\) is designed to accelerate to the
desired reference speed and maintain that desired speed primarily through control
of the vehicle’s accelerator, and controller \(h_2\) is designed to effect more rapid speed
reduction via the brake. Thus when the desired speed is less than \(0.25 \text{ m/s}\) of the
current speed, the brake is used, and otherwise the accelerator is used to control
speed (as in normal driving when releasing the accelerator reduces speed). These
controllers are provided sampled data at 20 Hz and are permitted to send new
updates to the CAT Vehicle at 20Hz.

The performance characteristics of each controller are provided for a change of
input as a step function of 1 m/s (-1 m/s for braking). The controller $h_1$ has a rise time of approximately 1.6 s with an overshoot of 5% and a settling time of approximately 5.52 s. The controller $h_2$ has a rise time of approximately 0.8 s, with an 11% overshoot and settling time of approximately 1.94 s.

Given the dynamics of the CAT Vehicle, a tradeoff must be performed on the comfort of the ride and the physical dynamics for a change in reference speed. The switching nature of the controller provides robustness to noise in sampled speed, since the accelerator is primarily used to control speed at steady state. Finally, the PID controllers are reset at 0 velocity, and standard approaches for windup avoidance are used to prevent unsafe acceleration [159].

5.3.4 Human driver controller

The driver who implements human control of the CAT Vehicle (coauthor M. Bunting) is instructed to attempt to maintain a desired velocity, but to slow down to avoid collision with the vehicle ahead. This is similar to the control law used in Experiment I, with the notable exception that the desired velocity is given in miles/hour (the primary readout of the speedometer in the CAT Vehicle). The driver received training from the University of Arizona on safe driving of high-occupancy vehicles, and had extensive practice to drive in this way, before the actual experiment is performed.

5.4 Experimental results: Dampening traffic waves with a single vehicle

The experimental results are presented in this section. To be able to effectively compare the results of the experiments, it is important to define metrics, which are consistent across the experiments. To this end, we present the metrics used to describe the traffic flow in Section 5.4.1. With the metrics fully defined, we present the results of the three experiments conducted in Section 5.4.2.
5.4.1 Definition and calculation of metrics

At each time step, we have the following data. From the image processing, we have the position \( x \), the velocity \( v \), and the acceleration \( a \) of each vehicle. From the OBD-II sensors, we have the instantaneous fuel consumption \( c \) of each vehicle. Let \( f_j^i \) denote the sample of a quantity \( f \), corresponding to vehicle \( i \), at time \( t_j \). A temporal average of a quantity over an interval \( t \in [t_{\text{start}}, t_{\text{end}}] \) is calculated as \( \bar{f}^i = \frac{1}{m} \sum_{j=1}^{m} f_j^i \), where \( f_1^i, \ldots, f_m^i \) are the samples of vehicle \( i \) in that time interval. Likewise, an average over all \( n \) vehicles at an instant \( t_j \) is given by \( \bar{f}_j = \frac{1}{n} \sum_{i=1}^{n} f_j^i \), where \( j \) denotes the time step. Finally, spatio-temporal averages are given by \( \bar{f} = \frac{1}{mn} \sum_{i=1}^{n} \sum_{j=1}^{m} f_j^i \).

The precise quantities of interest are defined next.

At each time instant the spatially-averaged instantaneous velocity is computed by summing the velocity of each vehicle \( i = 1, \ldots, n \) at a given time indexed by \( j \), and dividing by the number of vehicles as:

\[
\bar{v}_j = \frac{1}{n} \sum_{i=1}^{n} v_j^i.
\]

Over a given time interval with \( m \) velocity samples per vehicle, we compute the average (over all vehicles and over the time interval) as:

\[
\bar{v} = \frac{1}{mn} \sum_{j=1}^{m} \sum_{i=1}^{n} v_j^i.
\]

Similarly, we compute the velocity standard deviation of all vehicles and over the interval as:

\[
\sigma = \left( \frac{1}{mn - 1} \sum_{j=1}^{m} \sum_{i=1}^{n} (v_j^i - \bar{v})^2 \right)^{\frac{1}{2}}.
\]

Given the fuel consumption of vehicle \( i \) at time \( t_j \), the average (over all vehicles and over a time interval) consumption is computed as:

\[
\bar{c} = \frac{1}{mn} \sum_{j=1}^{m} \sum_{i=1}^{n} c_j^i.
\]
The throughput of traffic is computed as the product of the average velocity and the density (obtained from the number of vehicles and the length of the track \( L = 260 \text{ m} \)), and is given as:

\[
q = \frac{n}{L} \bar{v}.
\]

We also quantify braking events. Given a threshold deceleration \( \tau \), a brake event (deceleration peak) is defined as a contiguous region in time when \(-a_j^i > \tau\) that has the additional property that the signal \(-a_j^i\) must drop by more than \( \tau \) on either side of a peak. This deceleration peak count is encoded in the function \( \rho_\tau \), which takes the signal \( a_1^i, \ldots, a_m^i \) as an input, and outputs the number of peaks in that interval for vehicle \( i \). The final calculation of \( \kappa \), the rate of braking events, normalizes by the number of vehicles and total distance traveled (in kilometers). The threshold \( \tau \) is chosen as the average standard deviation of deceleration, taken over all vehicles in the uncontrolled interval when waves are active. This is computed as:

\[
\kappa = \frac{1}{n} \sum_{i=1}^{n} \frac{1}{x_m^i - x_1^i} \rho_\tau(a_1^i, \ldots, a_m^i),
\]

where \( \tau \) is always calculated over the interval when waves are active. The interval is determined based on the standard deviation of the velocity as outlined below.

The mean and standard deviation of the instantaneous vehicle velocities are computed at each timestep (i.e., for each timestep we compute the average of all vehicle speeds at that timestep, and then compute the sample standard deviation of all vehicle speeds at that timestep). When the standard deviation of the instantaneous vehicle velocities exceeds 2.5 m/s, the traffic is considered to contain a traffic wave. This threshold is used to define the time at which waves first appear in the traffic experiments. Figures 5.2a, 5.2b, and 5.2c show a timeseries of the instantaneous velocity standard deviation for Experiments I, J, and K, respectively with the threshold plotted in a red dashed line.
(a) Instantaneous standard deviation of vehicle velocities for Experiment I with dashed line indicating threshold for traffic waves in flow.

(b) Instantaneous standard deviation of vehicle velocities for Experiment J with dashed line indicating threshold for traffic waves in flow.

(c) Instantaneous standard deviation of vehicle velocities for Experiment K with dashed line indicating threshold for traffic waves in flow.

Figure 5.2: Instantaneous velocity standard deviation for all three experiments showing onset of traffic wave.
5.4.2 Experimental results

Experiment I contains 21 vehicles, including the CAT Vehicle. The CAT Vehicle is initially under human control, and the first traffic wave is observed 79 seconds into the experiment. The FollowerStopper wave-dampening controller is activated 126 seconds into the experiment, and set with a desired velocity of $U = 6.50 \text{ m/s}$. Over the next several minutes, the desired velocity is varied step by step to test the dependence of the traffic conditions on the set point. It is changed to 7.00 m/s (222 seconds into the experiment), 7.50 m/s (292 seconds into the experiment), and finally 8.00 m/s at 347 seconds into the experiment. At 415 seconds, the desired velocity is reduced to 7.50 m/s, where it remains for 48 seconds. At 463 seconds into the experiment, the human driver resumes control of the CAT Vehicle speed. The experiment is ended at 567 seconds.

Experiment J also involves 21 vehicles and follows a similar design as Experiment I. The main difference is that in Experiment J, after the wave initially appears, a trained human driver implements the control strategy described in Experiment I but without the aid of automation. The human-executed control strategy is to maintain a desired velocity, calculated by an external observer as the average velocity of the
previous lap, without colliding with the vehicle ahead. The CAT Vehicle is always under human control, but the driver switches from initially following the instructions given to all human drivers to mimicking the control strategy in Experiment I after a wave appears. A traffic wave is first observed 55 seconds from the start of Experiment J, and the active control to dampen the wave begins after 112 seconds at a desired velocity of 6.25 m/s (14 mph in the units displayed in the CAT Vehicle dashboard) with the command to “drive with an average speed of 14 miles per hour, unless safety requires slower speeds.” After 202 seconds, the CAT Vehicle operator is instructed to increase the desired speed “to 16 miles per hour,” (7.15 m/s) which is maintained for 98 seconds before reverting to typical human driving behavior. The experiment is ended after 409 seconds.

Experiment K is conducted with 22 vehicles. Note that one vehicle was added for this experiment, to demonstrate that instabilities and wave damping are not specific to having exactly 21 vehicles on the ring. At 161 seconds into the experiment, a traffic wave appears and is observed to travel against the flow at about 9.2 m/s. At 218 seconds, the PI controller with saturation wave damping controller is activated, and remains active until the end of the experiment at 413 seconds. Because the controller directly determines the desired velocity as part of the control algorithm, there are no external parameters that are changed during the experiment.

After conclusion of the experiments, the data gathered through a 360° camera placed at the center of track, in-vehicle devices, and CAT Vehicle control computers are analyzed to characterize the performance of each experiment with respect to dampening traffic waves.

Displacement data describe each vehicle’s distance traveled from their initial position on the ring at the beginning of the experiment. These data are extracted from the central camera using standard computer vision techniques to track vehicle positions along the ring. Velocity data are derived through discrete differentiation of displacement data (likewise, acceleration from velocity data) [9], which are validated against the CAT Vehicle control computers and the in-vehicle devices. The full data
set and code used to generate the plots can be found in [160].

Notable events in each experiment define time intervals over which to evaluate the state of traffic. In each analysis we quantify the traffic state according to (a) the standard deviation of traffic velocity; (b) the fuel consumption [161]; (c) the rate of excessive braking events; and (d) the traffic throughput. A detailed description of how these calculations are performed, as well as the specific definitions of common metrics of fuel consumption, velocity (average and standard deviation), and excessive braking are available in Section 5.4.1.

In Experiment I, the traffic state is quantified over eight time intervals throughout the experiment. In each interval, the fuel consumption, velocity standard deviation, excessive braking, and throughput are reported in Table 5.1. The position of each vehicle’s center over time is shown in Figure 5.3a, with the CAT Vehicle is shown in red and all other vehicles are shown in gray. In Figure 5.3b, the velocity profile of the CAT Vehicle is shown in red, and all other vehicle velocities are plotted in gray. For each interval, the black dashed line denotes the average velocity of traffic over that interval, and the blue dashed lines denote the average velocity plus/minus one standard deviation.

When the CAT Vehicle is initially under human control, a wave begins to appear and is observed to travel against the flow at approximately 9.2 m/s. After the controller is activated the wave is noticeably affected, but not fully removed, through the interval when the CAT Vehicle control is activated at a desired velocity of 6.50 m/s. The wave-dampening effect of the controller is observed in the velocity profiles (Figure 5.3b), which exhibit a lower magnitude of oscillation from the mean after control begins. When the CAT Vehicle desired speed set in the FollowerStopper is increased to 7.00 m/s 222 seconds into the experiment, further wave dampening is observed, and at a desired speed of 7.50 m/s, the best performance of the controller is achieved. Compared to the initial period where a wave was present under human control, the velocity standard deviation is reduced by 80.8%, the fuel consumption is reduced by 39.8%, and the excessive braking events are reduced from 8.58 events per
(a) Trajectories of all vehicles in Experiment I, CAT Vehicle shown in red.

(b) Velocity profiles of all vehicles (gray) and the CAT Vehicle (red) in Experiment I. Horizontal blue dashed lines are one standard deviation above and below the mean speed of traffic in the interval.

Figure 5.3: Trajectories and standard deviation in velocity for Experiment I.

Vehicle per kilometer to 0.12 events per vehicle per kilometer. Because the average velocity of traffic on the ring is also increased, the throughput on the roadway increases by 14.1%.

At 7.50 m/s, the CAT Vehicle’s speed matches the average traffic speed almost precisely, and consequently it does not need to slow down. However, at 347 seconds, the CAT Vehicle desired velocity is increased further to 8.00 m/s and the CAT Vehicle is, on average, faster than the flow of traffic—which inevitably induces a wave again. The reappearance of a wave has the effect of increasing fuel consumption relative to the slower desired velocities, but still represents a benefit of the control compared to the uncontrolled traffic. At 415 seconds the CAT Vehicle’s desired velocity is reduced to 7.50 m/s, and the wave is once again dampened. The FollowerStopper controller is deactivated after 463 seconds, and the traffic wave reappears.

The control of the CAT Vehicle has the impact of reducing the total fuel con-
Figure 5.4: Trajectories and standard deviation in velocity for Experiment J.

sumption of the traffic, as shown in Table 5.1. The lowest fuel consumption of 14.5 ℓ/100km is observed when the FollowerStopper is operated with the set point of 7.50 m/s. This is also the lowest fuel consumption amongst all experiments conducted. A video of Experiment I is provided in Movie S1 in the supplementary materials.

In Experiment J, the CAT Vehicle operator initially drives according to the same instructions as the other vehicle operators and a traffic wave appears at 55 seconds and is observed to travel against the flow at 8.6 m/s. At 112 seconds into the experiment, the CAT Vehicle operator begins to drive at a desired velocity of 6.26 m/s without colliding with the vehicle in front. Later the desired velocity is increased before returning to the gap closing instructions followed by all other human drivers. The trajectories are shown in Figure 5.4 and the traffic state is quantified in each interval in Table 5.2.

The dampening effect of the human-implemented controller is quantified by the standard deviation of the velocities, which is reduced by 49.5% when the 6.26 m/s control is active compared to when it is not. Similarly, excessive braking is reduced
<table>
<thead>
<tr>
<th>Interval</th>
<th>Time (s)</th>
<th>Velocity st. dev. (m/s)</th>
<th>Fuel consumption (ℓ/100km)</th>
<th>Braking (events/vehicle/km)</th>
<th>Throughput (veh/hr)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Exp. start</td>
<td>0</td>
<td>2.11</td>
<td>23.7</td>
<td>3.88</td>
<td>1665</td>
</tr>
<tr>
<td>Waves start</td>
<td>55</td>
<td>2.36</td>
<td>21.8</td>
<td>9.50</td>
<td>1828</td>
</tr>
<tr>
<td>Autonomy 6.26m/s</td>
<td>112</td>
<td>1.58</td>
<td>17.8</td>
<td>4.22</td>
<td>1822</td>
</tr>
<tr>
<td>Autonomy 7.15m/s</td>
<td>202</td>
<td>1.19</td>
<td>17.1</td>
<td>2.27</td>
<td>2008</td>
</tr>
<tr>
<td>Disable autonomy</td>
<td>300</td>
<td>2.25</td>
<td>20.6</td>
<td>9.43</td>
<td>1908</td>
</tr>
<tr>
<td>Exp. end</td>
<td>409</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
</tbody>
</table>

Table 5.2: Summary metrics over all vehicles by interval with corresponding start time, for Experiment J.

<table>
<thead>
<tr>
<th>Exp.</th>
<th>Velocity st. dev. (m/s)</th>
<th>Fuel consumption (ℓ/100km)</th>
<th>Braking (events/veh/km)</th>
<th>Throughput (veh/hr)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>WS CA %</td>
<td>WS CA %</td>
<td>WS CA %</td>
<td>WS CA %</td>
</tr>
<tr>
<td>A</td>
<td>3.31 0.64 -80.8 24.1 14.5</td>
<td>8.58 0.12 -98.6</td>
<td>1827 2085 +14.1</td>
<td></td>
</tr>
<tr>
<td>B</td>
<td>2.36 1.19 -49.5 21.8 17.1</td>
<td>9.50 2.27 -76.2</td>
<td>1828 2008 +9.8</td>
<td></td>
</tr>
<tr>
<td>C</td>
<td>3.85 1.74 -54.7 26.3 20.7</td>
<td>9.66 2.47 -74.4</td>
<td>1755 1711 -2.5</td>
<td></td>
</tr>
</tbody>
</table>

Table 5.3: Summary metrics of the flow in each experiment under the first interval when the traffic wave starts (WS) without wave dampening control, and under the best interval when control is active (CA). The percent change from WS to CA in each experiment is also reported.

The desired speed given to the CAT Vehicle driver also influences the reduction in the velocity variability. When the desired speed of the CAT Vehicle is increased to 16 mph (7.15 m/s), the standard deviation reaches the minimum values for the experiment. The throughput is also higher during this period compared to when the traffic is uncontrolled (2008 veh/hr vs. 1828 veh/hr). Once the CAT Vehicle returns to a typical gap closing behavior (i.e., no longer under human control to maintain a desired speed), the traffic wave reappears, and the velocity standard deviation increases.

When the CAT Vehicle is under wave dampening control by a human, the control reduces the overall fuel consumption when compared to the uncontrolled case (Table 5.2), where average fuel consumption (ℓ/100km) is recorded for each period of...
Interval | Time (s) | Velocity st. dev. (m/s) | Fuel consumption (ℓ/100km) | Braking (events/vehicle/km) | Throughput (veh/hr)
--- | --- | --- | --- | --- | ---
Exp. start | 0 | 1.62 | 18.9 | 1.11 | 2160
Waves start | 161 | 3.85 | 26.3 | 9.66 | 1755
Autonomy | 218 | 1.74 | 20.7 | 2.47 | 1711
Exp. end | 413 | - | - | - | -

Table 5.4: Summary metrics over all vehicles by interval with corresponding start time, for Experiment K.

the experiment. The result is a decrease in fuel consumption when the CAT Vehicle begins to dampen the traffic wave (a decrease from 21.8 ℓ/100km to 17.8 ℓ/100km, (18.3%)). A further decrease in fuel consumption (to 17.1 ℓ/100km, a decrease of 21.2% compared to when a wave is present initially) is observed when the desired velocity is increased from 14 mph (6.25 m/s) to 16 mph (7.15 m/s). Finally, when the CAT Vehicle returns to human-driven behavior and stops actively dampening the traffic wave, fuel consumption increases again and returns to a level similar to the pre-control fuel consumption (20.6 ℓ/100km) before control starts compared to (21.8 ℓ/100km) after control ends and the traffic wave reappears).

Finally, in Experiment K, an additional vehicle is added to the track, bringing the total number of vehicles to 22. As in other experiments, the CAT Vehicle begins the experiment in human control. The traffic is relatively smooth until the first strong wave occurs at 161 seconds. Comparing the traffic conditions under no control before the strong wave appears to when it is observed, the traffic wave results in a 37.7% increase in the average velocity standard deviation, a 39.3% increase in fuel consumption, and a 18.8% reduction in throughput.

At 218 seconds, the PI controller with saturation wave damping traffic controller is activated, and the wave is substantially reduced. Compared to the interval when the wave is present, the controller results in a reduction of the speed variability (54.7% reduction in standard deviation see Table 5.4). It also reduces the fuel consumption by 21.1%, and the rate of excessive braking is reduced by 74.4%. The
throughput is also slightly reduced by 2.5%. Note that this controller only uses information directly measured by the CAT Vehicle itself, and it does not require any external information. One consequence of this more local nature is that the wave dampening is not as perfect as in Experiment I. In particular, the controller slightly reduces the average velocity. Nevertheless, the velocity standard deviation, excessive braking, and fuel consumption are substantially reduced compared to when uncontrolled traffic waves are present.

By examining the trajectories (Figure 5.5), it is apparent that the control law is able to eliminate the initially present wave, but another wave is generated during the control period. The second wave is also damped by the control law, but its presence for a period of the active control accounts for the difference relative to the period where no waves occurred in the uncontrolled period at the start of the experiment.

In summary, all three controllers are shown to dampen human-generated traffic waves by controlling the CAT Vehicle to drive at the equilibrium velocity whenever safety allows. In Experiment I and B, an estimate of this equilibrium velocity is provided externally, and the estimate is updated several times throughout each experiment, causing the CAT Vehicle to first accelerate and then decelerate to adjust to the target velocity. In contrast, Experiment K, the control algorithm is designed to estimate the equilibrium velocity without external inputs.

These strategies are similar in theory to those used in VSL deployments discussed in the introduction and the result of these control strategies is less oscillatory traffic. However, in a typical VSL application, the speed limits are at fixed locations, but compliance with the speed advisory is not guaranteed. Moreover, the speed profile may change only at the spatial resolution of the changeable message sign installation, which may be expensive to deploy densely. In contrast, in the Lagrangian setting considered in this work, the control is achieved along the trajectory of the automated vehicle, which is directly enforced in experiments A and C (recall experiment B uses a human to implement the control, which would have compliance issues analogous to VSL approaches discussed in the introduction). Due to the similarities between
VSL and our approach, the experimental results indicate that VSL may be able to achieve similar results if the compliance rate is high enough.

The main result of the chapter should be viewed in terms of the penetration rate of automated vehicles. Although the presented experiments show that an AV is sufficient to eliminate the wave, on a long stretch of roadway the result corresponds to a penetration rate of AVs (around 5%). Moreover, the AVs should be distributed relatively uniformly in space. In the (more realistic) event that the AVs are not evenly spaced on the roadway, a higher AV penetration rate may be necessary to obtain the same wave-dampening effects.

To conclude, these experiments demonstrate that traffic flow control via low penetration rate automated vehicles is in fact possible. Moreover, the data collected quantify the benefits of conducting control via the AV. Specifically, under proper control, (a) the velocity standard deviation reduces noticeably; (b) the fuel consumption is reduced by a significant margin; (c) braking events are substantially reduced; and (d) in some experiments, even the average velocity (and thus the throughput) is increased (Table 5.3).

Velocity standard deviation: The velocity standard deviation is reduced in all experiments, ranging between 49.5% for Experiment J, 54.7% for Experiment K, and a high of 80.8% for Experiment I.

Fuel consumption: The fuel consumption in all experiments is reduced from when waves are present and under human control compared to when the autonomous car is active. The improvements include a reduction of 39.8%, 21.2%, and 21.1% in Experiments I, J, and K, respectively.

Excessive braking: The number of excessive braking events is also substantially reduced, from 8.58 to 9.66 excessive braking events/veh/km down to 2.47 events/veh/km in the worst performing controller and nearly complete elimination (0.12 events/veh/km) in the best performing controller.

Throughput: Changes in throughput for each experiment are +14.1% for Experiment I, and +9.8% for Experiment J, with a −2.5% change in Experiment K.
It is worth noting that the wave speed in Experiments I-K were roughly 1.5 times greater than the waves observed in the experiment of [1]. This is likely since the wave speed is a function of the vehicle length and minimum gap. While the vehicle lengths are not provided in [1] and [162], in subsequent experiments the vehicles were selected to have the same length of 3.89 m [162]. This is substantially smaller than the average vehicle length in the experiments presented in this chapter (4.81 m for Experiments I and J and 4.82 m for Experiment K), and likely the cause for the faster wave observed.

5.5 Conclusions

AVs can revolutionize the control of traffic flow. They offer the potential to shift from localized control measures, like ramp metering, and centralized ones, as variable speed limit gantries, to Lagrangian actuators immersed in the traffic stream. Strikingly, it is not necessary for all vehicles to be automated in order to bene-
fit from mobile actuation. A single autonomous vehicle can control the flow of at least 20 human-controlled vehicles around it, with substantial reductions in velocity standard deviation, excessive braking, and fuel consumption.

Moreover, this study demonstrates that these benefits can be achieved via structurally very simple control strategies, based only on the AV’s velocity, its spatial gap between the vehicle immediately in front, and some estimate of the average velocity of traffic flow. The *PI with saturation* controller (Experiment K) is a fully automatic control, while the *FollowerStopper* (Experiment I) and the human-implemented control (Experiment J) have an external input (dependent on observed traffic conditions). This simple structure implies that a noticeable impact on congested traffic flow can in principle be achieved by means of adaptive cruise control systems that are already in place in certain new vehicles, and the use of intelligent infrastructure and/or connected vehicles to provide the required external inputs.

Most contemporary traffic control strategies (implemented in practice, and/or proposed in the literature) are based on centralized interventions, such as ramp-metering, variable speed limits, and traffic light controls. For example, a successful variable speed limit control may yield a 5% increase in capacity [131]. However, those traditional control approaches will always have limited effect on the traffic dynamics that emerge between the fixed control points. In contrast, the control of traffic flow via a sparse set of Lagrangian actuators (AVs or trained human drivers) enables new opportunities for control, with a direct positive effect on the dynamics of traffic flow, and without the need of a dedicated actuation infrastructure.

The presented ring experiments approximate a stretch of single-lane roadway, with AVs uniformly spaced and with connectivity to share information about the traffic state ahead. However, the theory extends also to multi-lane freeways, on which lane changing can serve as an additional trigger of stop-and-go waves. The lane changes can also open up gaps in the vacated lane, which can serve to dampen waves in that lane. The central challenge in the multi-lane setting is to have controllers that dynamically dampen waves, but without leaving too large gaps, because
large gaps may trigger additional lane changing, which may reduce the effectiveness of the strategy. The results of Experiment I demonstrate that the controller does in fact not leave a large gap once the waves have been damped. To fully quantify the benefits of Lagrangian actuators on urban freeways, future multi-lane experiments are needed.

The control of complex multi-agent systems has impact beyond vehicular traffic flow, including coordinated robots [163], social networks [164], animal swarming [165, 166], and many other applications. However, in contrast to many applications in robotics or fleet control, the human agents play a crucial role in traffic flow dynamics. Moreover, in contrast to other human-in-the-loop cyber-physical systems, the automated controller and the human agents are spatially separated, and they do not work cooperatively. Rather, the AVs counteract the humans’ tendency to produce unstable traffic situations. The results shown here imply that this concept is not a far future but instead could be, in principle, implemented with already existing technology.
Chapter 6

Reducing vehicle emissions by stabilizing traffic flow

6.1 Introduction

It is expected that in the next few years vehicles will be developed with enhanced automation capabilities, and soon autonomous vehicles (AVs) will begin entering the vehicle fleet in small numbers. Even at low penetration rates (e.g., as low as 5% under ideal circumstances), these vehicles may be capable of dampening traffic waves caused by human driving behavior, resulting in smoother driving profiles (e.g., reduced acceleration/deceleration and speed variability) and consequently smoother traffic flow conditions compared to entirely human-piloted traffic [13]. Smooth driving profiles result in lower fuel consumption and emissions that are damaging to the environment and to human health [167].

The main focus of this chapter is to quantify the potential reduction of vehicle emissions of the total traffic flow when a small fraction of vehicles are automated and designed to dampen human-generated stop-and-go traffic. This work uses experimental traffic of Experiments I, J, and K in Chapter 5 where a single autonomous vehicle is carefully controlled to dampen stop-and-go waves that arise when human-piloted traffic is sufficiently dense. The reduction in emissions of the total traffic
flow are estimated from the experimental data using the *Motor Vehicle Emissions Model* (MOVES) [168]. While the introduction of AVs at large penetration rates is certain to induce large effects such as changes in land use [169], travel demand [4], mode choice [170], and vehicle ownership [171], here we consider the impact that a small penetration rate of carefully controlled AVs can have on emissions due to the stability of the resulting traffic flow. By holding constant other large but longer term effects, we are able to highlight that the effects on the flow stability and consequently the emissions of the flow is itself significant (i.e., up to 73% for some emissions categories). The main result suggests that the design of the automation controllers will be important to overall traffic emissions long before the entire fleet is automated.

### 6.1.1 Related work on air quality and vehicle emissions

Motor vehicle emissions are a primary source of greenhouse gasses and contribute to global climate change [172]. These emissions are made worse by congestion and stop-and-go traffic [173]. Recently, a broad range of efforts have been made to curb vehicle emissions [174]. These efforts include vehicle improvements to increase the efficiency of combustion engines [175, 176] and a transition to hybrid vehicles [177, 178]. It also includes traffic network management strategies that have focused on more efficient vehicle routing and traffic control [179, 180, 181]. It is anticipated that AVs will also impact vehicle emissions, though it is unclear whether they will increase or decrease overall traffic emissions [182, 183].

Direct measurement of vehicle emissions has been an area of intense research interest for several decades [184, 185, 186, 187]. However, due to the large cost associated with emissions measurement equipment, there has been a significant push [188, 189, 190] to develop models that are able to estimate vehicle emissions based on easier to measure quantities such as vehicle speed and acceleration. These models estimate the vehicle emissions for a variety of pollutants (e.g., carbon dioxide, carbon monoxide, hydrocarbons, and nitrogen oxides).
These emissions models generally fall into one of two categories: aggregate and microscopic. Aggregate models are used to assess the environmental impact during project planning and use inputs such as average link-level speed and distance traveled to assess emissions. These models are often useful for assessing the impact of a large change in land use and traffic patterns on city or regional emissions. Popular aggregate models include the US Environmental Protection Agency (EPA) MOVES [168] and MOBILE6 [191] as well as the European Environment Agency COPERT [192] and ARTEMIS [193] models. In contrast, microscopic emissions models use instantaneous measurements at the vehicle level to estimate emissions for a specific trip. Common microscopic emissions models include CMEM [190], EMIT [194], POLY [195], and VT-Micro [188, 189, 196]. These models are typically used for estimating emissions of individual vehicles under some specified drive cycle or test procedure.

The CMEM model [190] was developed using the National Cooperative Highway Research Program emissions database. The instantaneous tailpipe emissions are estimated as a function of the fuel rate, the engine-out emissions index, and the catalytic pass fraction. The model has been used in several works to estimate instantaneous vehicle emissions [197, 198, 199].

The EMIT model [194] is similar to the CMEM model in that the tailpipe emissions are modeled as the product of the output of an engine-out model and a catalytic pass fraction. The engine-out model computes the fuel consumption as a function of speed and acceleration, while the catalytic pass fraction is emissions-type specific and determined through a regression analysis.

Similarly to the EMIT model, the VT-Micro model [188, 189, 196] uses polynomial regression with instantaneous velocity and acceleration as inputs to estimate vehicle emissions. The regression model for each type of emission uses calibrated parameter values for terms that are constant, linear, quadratic, and cubic in both velocity and acceleration. This allows for the model to capture the high degree of non-linearity in vehicle emissions which have been shown in several works including
those of [196] and [197].

In addition to the quantities used in the models described above, some models compute *vehicle-specific power* (VSP), the total instantaneous power demand of the vehicle normalized by the mass of the vehicle. One such model is the POLY emissions model [195], which uses vehicle speed, acceleration, and VSP as explanatory variables for a regression model to estimate vehicle emissions. Vehicles are assigned a category based on vehicle size, model year, and emitter type, and a regression model is learned for each pollutant. Note that due to the structure of the regression, the POLY model is able to incorporate historical acceleration information into the model prediction.

The MOVES model offers both an aggregate analysis as discussed above as well as a VSP-based analysis that allows for instantaneous emissions modelling at the individual vehicle level. It is a state-of-the-science emission modeling system that estimates emissions for mobile sources for air pollutants. The aggregate approach provided by MOVES estimates vehicle emissions based on a mapping between average travel speed and emission rates. The VSP-based approach estimates vehicle emissions by utilizing relationship between engine load and vehicle emissions at a high time-resolution (1Hz), and is capable of assessing the influence of transient vehicle dynamics on engine load and emissions. Therefore, this approach is suitable to analyze vehicles emissions on an ad-hoc road link or segment as has been done in previous studies integrating vehicle travel profiles with the MOVES model to investigate air quality benefits of various traffic management or control technologies. For example, see the works by [200, 201, 202], and [203]. In these studies, vehicle travel profiles were obtained through either traffic simulation or real-world data collection. Furthermore, the MOVES model is regularly maintained and updated by EPA to reflect emission characteristics and improvements of emissions control techniques future vehicles. The analysis in this chapter relies on emissions estimates from a VSP analysis conducted in MOVES.
6.1.2 Related work on improving air quality and reducing emissions through traffic control

and can reduce the throughput and increase the fuel consumption of all vehicles on the roadway [13].

The ability of AVs to reduce emissions has been considered by several simulation-based works reviewed below [198, 204]. Liu et al. [204] modified a typical vehicle speed profile, and applied smoothing techniques to produce a plausible synthetic AV driving profile. The emissions estimates of both the original (oscillatory) and the smoothed velocity profile are compared using MOVES, and it is found that AV emissions may be substantially reduced. Compared to the present work, Liu et al. [204] does not consider field data captured from vehicles. Moreover, it only considers the direct benefits of a smooth driving profile on the emissions of the AV, and does not capture the potential of AVs to also reduce the emissions of human piloted vehicles due to the smoother driving profile the AVs may propagate to human drivers.

Yang et al. [198] propose a control framework to provide advisory speeds to a subset of vehicles with the goal to smooth the traffic flow. The framework is modeled in simulation at varying AV market penetration rates ranging from 1% to 100%. Human-piloted traffic is simulated using a car-following model, and some vehicles implement a green driving strategy to dampen traffic waves a feedback-based cooperative adaptive cruise control (CACC) The output from the simulation is analyzed using the CMEM model to estimate the fuel consumption and emissions. They find that at a 5% penetration rate of CACC-equipped vehicles in the traffic, hydrocarbon and carbon monoxide emissions are reduced by about 60%, while carbon monoxide emissions are reduced by as much as 73% and carbon monoxide emissions are reduced by 9%. In agreement with the experimental findings presented in this chapter, the simulation results of [198] indicate a reduction in emissions and fuel consumption is possible with the introduction of a small number (e.g., \(~5\%\)) vehicles that
actively dampen the traffic flow.

In contrast to enforcing specific speed profiles using AVs or ACC vehicles the ability of advisory speed limits to calm traffic and reduce emissions has also been studied. Severin et al. [205] study the use an advisory speed to smooth traffic and quantify the effect of the advisory speed on vehicle emissions of the traffic flow. Using traffic simulation and the CMEM model, they study varying rates of vehicles that follow the advisory speed, and determine that while the advisory speed may not significantly impact the travel time, it can have a significant impact in reducing vehicle emissions and fuel consumption. Severin et al. [205] find a 35% reduction in carbon dioxide emissions, a 85% reduction in carbon monoxide emissions, a 69% reduction in hydrocarbon emissions, and a 74% reduction in nitrogen oxide emissions when all vehicles follow the advisory speed limit.

### 6.1.3 Contribution and outline

The works discussed above provide simulation results to give insight into the possible reduction in emissions that may result from even just a small portion of the vehicle fleet becoming autonomous. In contrast, this chapter uses experimental data from [13] presented in Chapter 5, to analyze the impact of a single AV on the vehicle emissions of all of the vehicles in the traffic flow. Thus, this work goes beyond the previously mentioned simulation results since it uses experimental data to demonstrate the ability of AVs to reduce emissions if properly controlled.

This chapter presents experimental evidence of the impact of oscillatory traffic on emissions, and quantifies the potential emissions reductions possible if the waves are mitigated using automated vehicles. This is accomplished by measuring vehicle trajectories in a series of experiments on a circular ring road similar those of [1], and estimating the microscopic vehicle emissions using the VSP analysis in MOVES. Furthermore, three control strategies are implemented on a single AV in the flow of mostly human-piloted vehicles to control the flow and dampen traffic waves. The three control strategies give an indication of the variability of the potential benefits
due to the implementation of the precise control law implemented by the AV. The reduction in emissions due to the control action of a single autonomous vehicle (∼5% of the traffic stream in the experiments) is presented in this chapter. To identify if the benefits observed are due to the vehicles used in the experiments, or if there will still be benefits in the future when the fleet mix changes, we consider four fleet scenarios that include the vehicle fleet tested in the experiments as well as projected fleets in the future. Full details of the four scenarios considered are presented in Table 6.1.

The main contribution of this work is to quantify the reduction in total traffic emissions possible when a single autonomous vehicle in a flow of 20 to 21 human-piloted vehicles is driven to dampen the traffic waves present in the flow. We find that driving a single autonomous vehicle in such a way as to dampen traffic waves can reduce traffic emissions of the entire traffic flow by over 70%.

6.2 Methodology

In this section, the methodology used in the experimental design and execution, as well as data analysis is briefly summarized. Full details on the experimental design and setup, as well as a detailed discussion of the traffic controllers used in this experiment are presented in Chapters 3 and 5. First, we describe the experimental setup, next we describe the wave-dampening controllers tested, and finally we briefly summarize the model used to estimate vehicle emissions.

6.2.1 Experimental setup

The vehicle trajectories used to estimate vehicle emissions in this chapter are obtained from the experiments described in Chapter 5 and [13]. The experiments consist of between 21 and 22 vehicles driving on a single lane ring track. The experiments are designed to have a similar vehicle density as the experiment conducted by [1].
At the beginning of each experiment, vehicles are spaced evenly on the track, with the number of vehicles between experiments varying from 21 to 22 vehicles depending on the desired density. Hired drivers are instructed to drive as they would in regular traffic, and to follow the vehicle in front of them safely. Individual tests last between 5 and 10 minutes, with breaks between to reset the track and allow for drivers to rest.

A single vehicle in the experiment, the CAT Vehicle, is a highly instrumented and actuated vehicle that can be switched from being human-piloted to autonomous. In each experiment, the CAT Vehicle begins under human control with a driver who is given the same instructions as all other drivers. Once traffic waves develop, the driving behavior of the CAT Vehicle is changed by either switching the CAT Vehicle into an autonomous driving mode (Experiments I and K), or by instructing the driver of the CAT Vehicle to drive with a specific velocity (Experiment J). These experiments allow data collection on traffic in which stop-and-go waves appear due to human driving behavior, and are subsequently dampened or eliminated via control of a single vehicle on the track, which represents a scenario in which roughly 5% of vehicles are either autonomous, or driving an a way that is substantially different from the human drivers.

The experiment is recorded by a 360-degree panoramic camera placed at the center of the circular track. Video recordings from the center 360-degree camera are used to extract vehicle trajectory data through computer vision algorithms. The computer vision algorithm uses background subtraction and pixel clustering, and template tracking to identify the position of each vehicle on the track in each frame. The resulting vehicle trajectories are verified against human-labeled data to an accuracy of 0.11 m.

6.2.2 Dampening traffic waves

Recall from Chapter 5 that a total of three control approaches implemented on the CAT Vehicle are tested. All controllers share the goal to stabilize the entire traffic
flow such that all vehicles, including the human-piloted vehicles, drive with as little velocity variation as possible. The general strategy employed by all three methods is to command the AV to drive with a properly selected velocity, and to drive with as uniform of a velocity profile as possible while still operating the vehicle safely. If this uniform velocity is close to the equilibrium velocity \([206]\) of the traffic flow, the AV allows a small gap to open up as the vehicles race away when they exit a traffic wave, and is able to use this gap to avoid braking when the vehicles in front enter a traffic wave. If properly chosen, this allows the AV to approach the lead vehicle just as it is leaving a traffic wave, and thus dampens the wave. The controllers that are run on the CAT Vehicle are briefly summarized in this section. See Chapter 5 for a detailed explanation of each controller.

**Controller A: FollowerStopper controller**

The premise of this controller is to command exactly the desired velocity whenever safe (i.e., as in a standard cruise controller), but to command a suitable lower velocity whenever safety requires, e.g., to avoid colliding with the lead vehicle. Using the gap to the lead vehicle (defined as the distance from the front bumper of the AV and the rear bumper of the lead vehicle) and the velocity difference between the lead vehicle and the AV, three regions are defined: (i) a safe region, where the AV drives at the desired speed, (ii) a stopping region, where a zero velocity is commanded, and (iii) an adaptation region, where some average of desired and lead vehicle velocity is commanded. These regions allow the AV to select a safe velocity, while driving as smoothly as possible. The full details on the calibration and implementation of the FollowerStopper controller are provided in the work by \([13]\).

**Controller B: Traffic control with a trained human driver**

One experiment is conducted where a trained human driver is instructed to drive at a specified speed and only deviate when safety mandates. The speed at which the driver is instructed to drive is computed externally by experimental staff observing
the experiment. It is computed as the total length of the track divided by the time for the CAT Vehicle to make one complete pass around the track. This speed is then communicated to the driver of the CAT Vehicle via two-way radio.

**Controller C: PI controller with saturation**

The idea behind this controller is that the CAT Vehicle may estimate the average speed of the vehicles in front, and drive as close to that average speed as safely possible. When stop-and-go waves are present, it allows a gap to open up in front of the CAT Vehicle when the lead vehicle accelerates, which is then closed when the lead vehicle decelerates as it enters the next wave. An estimate of the average speed required by the controller can be obtained through connectivity with other AVs in the flow ahead of the CAT Vehicle. The controller determines a command velocity for the AV following a standard proportional integral (PI) control logic where the deviation from the average speed is treated as the error signal in the PI controller. More information about the general structure of PI controllers can be found in [157]. The PI controller is modified to include a saturation effect, in which the CAT Vehicle should command the velocity of the lead vehicle for safety reasons when the gap is small.

**6.2.3 Estimating vehicle emissions**

In this work, the operating mode based project level analysis module in MOVES is used to evaluate vehicle emissions and assess emission benefits of replacing roughly 5% of the traffic flow with AVs that are specifically designed to stabilize the traffic flow. The EPA regularly maintains and updates the MOVES model to reflect emissions characteristics and improvements in emission control technologies in new and future vehicles. This feature of MOVES is important since the scenarios we consider include the impacts that AVs may have both currently and future years.

The MOVES model predicts vehicle emissions based on five different parameter values. These parameters are the humidity and temperature, the road link that
the modelling is being conducted on, the vehicle fleet mix, the vehicle fleet age distribution, and the VSP distribution during the drive cycle. These parameters are explained in more detail below.

1. Humidity and Temperature: Meteorological conditions influence vehicle engine performance and thus will effect vehicle emissions. The simulation time and location are set to the same as the experiment time and experiment location: Tucson, Arizona in July. This takes into account average high temperatures and precipitation in Tucson, Arizona in July.

2. Road Link: We assume each experiment is one road link. The length of each road link is computed as the average distance each vehicle drove during the experiment. It is important to note that since the total emissions on that road link are normalized by the length of the road link, the link length does not impact emission rates per distance, but does impact the total emissions of the fleet on the link.

3. Vehicle fleet mix: In this study, we only consider the light-duty vehicle fleet, which consists of sedans and light-duty trucks (e.g., SUVs and small pickup trucks). These two types of vehicle are different in size, weight, engine capacity, etc., and therefore have different emission characteristics. The vehicle fleet mix used in this study is either the actual fleet mix used to experimentally collect the vehicle trajectories (Scenario 1 discussed in Section 6.2.4) or based on fleet mix projections (Scenarios 2-4) as discussed in Section 6.2.4.

4. Vehicle fleet age distribution: Emissions of vehicles vary based on age of vehicles due to an effect known as emissions deterioration [207]. Specifically, emissions per distance tend to increase as vehicles age. Therefore, it is important to know the age distribution of vehicle fleet to account for aging effect in our emission analysis. We adopted the default age distribution in MOVES, which specifies vehicle age distribution projections through the year 2050. The MOVES model assumes a distribution between 0 and 30 years of age.
<table>
<thead>
<tr>
<th>Scenario</th>
<th>Electric vehicle fraction (%)</th>
<th>Sedan fraction (%)</th>
<th>Small truck fraction (%)</th>
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<td>57.2</td>
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</table>

Table 6.1: Four scenarios considered including 1) the vehicle fleet tested in the 2016 experiment, 2) US national vehicle fleet in 2016, 3) the projected 2030 vehicle fleet, and 4) the projected 2050 vehicle fleet, assuming an 80% vehicle electrification, spread evenly across both vehicle classes.

5. VSP Distribution: For each experiment, the instantaneous velocity and acceleration is obtained from the experiments by [13]. Using these measurements, the corresponding VSP is calculated at 1 Hz VSP and then aggregated to obtain VSP distribution over time. For typical light-duty vehicles and trucks, VSP in units of kW/ton can be approximated using (6.1) where $v$ is the vehicle velocity in mph, $a$ is the vehicle acceleration in mph/s. This equation models work required due to acceleration of the mass of the vehicle, rolling friction, and air drag, but does not consider non-driving related energy consumption such as air conditioning.

$$VSP \approx \phi_1 va + \phi_2 v + \phi_3 v^3, \quad (6.1)$$

where $\phi_1 = 0.22$, $\phi_2 = 0.0954$, $\phi_3 = 0.0000272$ [208]. Using this approximation for all vehicles neglects small differences in air resistance due to vehicle form or rolling resistance due to tire pressure.

6.2.4 Vehicle fleet scenarios considered

The effect on vehicle emissions of a small number of AVs in the traffic flow will depend to a large extent on the vehicle fleet on the road, and the levels of emissions they produce. Therefore, a total of four scenarios with different fleets are considered.
These scenarios are detailed in Table 6.1.

In Scenario 1, the vehicle fleet used during the experiments is considered, where 45.5% of the vehicles are sedans, 54.5% are SUVs, and no electric vehicles (EVs) are present. In Scenario 2, the average 2016 vehicle fleet in the US is considered where 51.2% of the vehicles are sedans, 48.8% are SUVs, and a negligible percentage of the vehicles are electrified. Scenario 3 considers the projected 2030 vehicle fleet in the US where 44.5% of the vehicles are sedans and an estimated 3.4% of the vehicle fleet is electrified, distributed evenly between sedans and SUVs, as projected by the US Energy Information Administration’s 2017 Annual Energy Outlook [209]. Finally, in Scenario 4 the projected 2050 vehicle fleet in the US is considered with 42.8% sedans assuming a very high electric vehicle adoption rate of 80%. This fleet also takes into account the vehicle age distribution for Scenarios 2, 3, and 4, while the vehicle age distribution in Scenario 1 is obtained from the vehicle fleet used to conduct the experiments.

6.3 Experimental results

Recall from Chapter 5 that each experiment is executed on the 260 m circular track and in each experiment all vehicles begin under human control. After some time, traffic waves naturally emerge. These waves are allowed to persist without taking action to dampen them for a few minutes. Some time later, a dampening action is taken by the CAT Vehicle, which is maintained for a period of time. This dampening action takes the form of vehicle automation in Experiments I and K, and a trained human driver smoothing the traffic flow in Experiment J. In Experiments I and J, some time later the dampening action is ended and traffic waves emerge again. In Experiment K, the experiment is ended while the dampening action is still in effect.

Specifically, in Experiment I, the FollowerStopper controller is used to dampen traffic waves, while in Experiment J a human driver is instructed to drive the CAT Vehicle at a constant speed, and in Experiment K a PI controller with saturation is
used to dampen traffic waves. In all experiments, the result of the control algorithm is to reduce the velocity standard deviation as seen in the vehicle trajectories in Figures 6.1, 6.2, and 6.3 for Experiments I, J, and K, respectively.

Vehicle emissions rates for hydrocarbons (HC), carbon monoxide (CO), carbon dioxide (CO\(_2\)), and nitrogen oxides (NO\(_x\)) are obtained through MOVES for each of the three experiments. While there are several controller periods tested in each experiment, for the purposes of this analysis only the period when waves are present and the period where the AV controller is most effective are used.

### 6.3.1 MOVES operating mode distribution

The MOVES analysis is based on the percentage of time in each drive schedule that is spent in a particular operating mode. These operating modes are specified based
Figure 6.2: Vehicle trajectories for all vehicles in Experiment J color coded by, velocity (top), and acceleration (bottom). The time under which traffic waves are present is shaded blue, while the control period used for analysis, where the AV is actively dampening traffic waves is shaded red.
Figure 6.3: Vehicle trajectories for all vehicles in Experiment K color coded by, velocity (top), and acceleration (bottom). The time under which traffic waves are present is shaded blue, while the control period used for analysis, where the AV is actively dampening traffic waves is shaded red.
on vehicle specific power and velocity, and consequently it is possible to classify each moment of the drive schedule as one of a number of discrete operating modes, which correspond to vehicle emissions. Specifically, the percent of time spent in each operating mode over the course of a drive schedule along with the total distance traveled and the average travel speed determine the vehicle emissions estimate. The operating modes are outlined in the MOVES documentation [168].

The operating mode distributions for each experiment are separated for the period when traffic waves are present and the period when the AV is actively dampening the traffic flow, and plotted in Figures 6.4a through 6.4c. A greater percentage of the time is spent in higher operating modes when waves are present than when the AV is actively dampening the waves.

As seen in Figure 6.4a through Figure 6.4c, when comparing the MOVES operating mode distribution under uncontrolled conditions when traffic waves are present (left) to the operating mode distribution when the CAT Vehicle is actively dampening the traffic flow (right), the operating mode distribution shifts from higher operating modes to lower operating modes. These lower operating modes are indicative of lower engine demand, and thus generally correspond to lower vehicle emissions. This is because there is less positive acceleration across the vehicle fleet when the CAT Vehicle is actively dampening the traffic flow, and thus lower VSP.

6.3.2 Scenario 1: Estimating emissions of the experiment fleet

We estimate the emissions of the experimental fleet as tested in three different experiments. We consider the reduction of emissions when a single vehicle in the traffic flow is an AV, and consider three different control strategies, one in each of the three experiments. In Experiment I, the average per-vehicle emissions in the experiment (Scenario 1) in the presence of traffic waves for hydrocarbons is 0.010 g/mi, for carbon monoxide are 2.430 g/mi, for nitrogen oxides are 0.107 g/mi, and for carbon dioxide are 1245 g/mi. When the traffic is under the control of the AV in the control period when the set speed is 7.50 m/s, the hydrocarbon emissions
Figure 6.4: Distribution of MOVES operating modes in each of the three experiments when waves are present (left) and when the AV is actively dampening the traffic waves (right). In all three subfigures, a broader range of operating modes is observed when the traffic wave is present (left) than when the AV is actively dampening the traffic waves (right). Furthermore, the prominent operating modes present when the AV is dampening the traffic waves are those that correspond to lower vehicle emissions. Note that while the MOVES model defines operating modes above 25, these operating modes are not observed in any of the experiments, and thus left off of these figures for plotting purposes.
are reduced by 51.5% to 0.005 g/mi, the carbon monoxide emissions are reduced by 39.1% to 1.481 g/mi, the nitrogen oxide emissions are reduced by 73.5% 0.028 g/mi, and the carbon dioxide emissions are reduced by 30.7% to 863.1 g/km.

In Experiment J, the average per-vehicle emissions when a traffic wave is present in the vehicle fleet tested in the experiment (Scenario 1) are as follows: hydrocarbon emissions are 0.010 g/mi, carbon monoxide emissions are 2.380 g/mi, nitrogen oxide emissions are 0.095 and the carbon dioxide emissions are 1260 g/mi. When the AV is actively dampening the traffic waves, the hydrocarbon emissions are reduced by 38.7% to 0.006 g/mi, the carbon monoxide emissions are reduced by 36.1% to 1.520 g/mi, the nitrogen oxide emissions are reduced by 60.8% to 0.037 g/mi, and the carbon dioxide emissions are reduced by 27.2% to 916.0 g/mi.

In Experiment K, the average per-vehicle emissions in the presence of a traffic wave for Scenario 1 is 0.101 g/mi for hydrocarbons, 2.420 g/mi for carbon monoxide, 0.101 g/mi for nitrogen oxides, and 1240 g/mi for carbon dioxide. When the AV is actively dampening the traffic flow hydrocarbon emissions are reduced by 63.8% to 0.006 g/mi, carbon monoxide emissions are reduced by 26.9% to 1.770 g/mi, nitrogen oxide emissions are reduced by 63.3% to 0.037 g/mi, and carbon dioxide emissions are reduced by 14.8% to 1060 g/mi.

6.3.3 Scenario 2: Emissions of the 2016 vehicle fleet

In Scenario 2 which represents the average US fleet in 2016, the average per-vehicle emissions in Experiment I in the presence of traffic waves are 0.191 g/mi HC, 7.843 g/mi CO, 0.933 g/mi NOx, and 1413 g/mi CO2. When the AV is actively dampening the traffic flow, the HC emissions are reduced by 38.4% to 0.125 g/mi, the CO emissions are reduced by 38.1% to 4.854 g/mi, the NOx emissions are reduced by 64% to 0.336 g/mi, and the CO2 emissions are reduced by 31.4% to 970 g/mi.

In Experiment J, in the presence of a traffic wave the average per-vehicle HC emissions are 0.189 g/mi, the average carbon monoxide emissions are 7.740 g/mi, the average nitrogen oxide emissions are 0.872 g/mi, and the average carbon diox-
ide emissions are 1420 g/mi. When the AV is actively dampening the traffic waves hydrocarbon emissions are reduced by 28.0% to 0.136 g/mi, carbon monoxide emissions are reduced by 34.6% to 5.060 g/mi, nitrogen oxide emissions are reduced by 53.0% to 0.411 g/mi, and carbon dioxide emissions are reduced by 27.5% to 1030 g/mi.

In Experiment K, when traffic waves are present the average per-vehicle hydrocarbon emissions are 0.191 g/mi, the carbon monoxide emissions are 7.760 g/mi, the nitrogen oxide emissions are 0.884 g/mi, and the carbon dioxide emissions are 1410 g/mi. When the AV is actively dampening traffic waves hydrocarbon emissions are reduced by 17.8% to 0.157 g/mi, carbon monoxide emissions are reduced by 24.7% to 5.840 g/mi, nitrogen oxide emissions are reduced by 52.0% to 0.424 g/mi, and carbon dioxide emissions are reduced by 15.5% to 1190 g/mi.

Figures 6.5a through 6.5d show that the hydrocarbon, carbon monoxide, and nitrogen oxide emissions for Scenario 2 are substantially higher than in Scenario 1. This is because the vehicle fleet used in Scenario 1 was mostly 2016 and 2015 model year vehicles (full details on the vehicles used can be found in [13]) while Scenario 2 is composed of the US age distribution of vehicles in 2016. Since most of the vehicles are less than three years old, very little emissions deterioration has occurred, and the estimated emissions for that scenario were very low. Scenarios 2 through 4 use projected fleet age distributions, which assume a mix of new and old vehicles on the road. In the scenarios tested, the older vehicles may be polluting more than the newer vehicles due to emissions deterioration. This is not the case in the vehicle fleet tested in the 2016 experiment since most vehicles are new.

6.3.4 Scenarios 3 and 4: Emissions of projected future fleets

The projected future vehicle fleet scenarios presented in Table 6.1 are also considered. The emissions for these scenarios are presented below. In Scenario 3, the projected 2030 US vehicle fleet us used for estimation. In Experiment I, B, and C the hydrocarbon emissions in the presence of traffic waves are 0.019 g/mi, 0.018
g/mi, and 0.019 g/mi, respectively. When the Autonomous vehicle is actively dampening the traffic waves, the reductions in hydrocarbon emissions for Experiment I, J, and K are 38.4% to 0.010 g/mi, 37.8% to 0.011 g/mi, and 35.1% to 0.012 g/mi, respectively. Similarly, for Experiment I, J, and K, the carbon monoxide emissions in the presence of traffic waves are 2.984 g/mi, 2.920 g/mi, and 2.960 g/mi, respectively. When the AV is actively dampening the traffic flow, carbon monoxide emissions are reduced by 39.3%, 36.1%, and 27.1% to 1.812 g/mi, 1.860 g/mi, and 2.160 g/mi for Experiment I, J, and K, respectively. In the presence of a traffic wave, the nitrogen oxide emissions for Experiment I, J, and K are 0.114 g/mi, 0.101 g/mi, and 0.107 g/mi, respectively. By actively dampening the traffic flow, the AV is able to reduce the average vehicle emissions for Experiment I, J, and K by 72.5%, 59.8%, and 61.0% to 0.031 g/mi, 0.041 g/mi, and 0.041 g/mi, respectively. Finally, when traffic waves are present, the average per-vehicle emissions of carbon dioxide for Experiment I, J, and K are 1019 g/mi, 1030 g/mi, and 1010 g/mi, respectively. When the AV is actively dampening the traffic flow, these are reduced by 31.0%, 27.3%, and 15.1% to 703.0 g/mi, 748.0 g/mi, and 15.1 g/mi, respectively.

In Scenario 4, the projected average US vehicle fleet for 2050 is used for estimation. However, a high electric vehicle adoption rate of 80% electric vehicles is also assumed. This is to test how significant the impact of AVs dampening the traffic flow will be on emissions with a high vehicle fleet electrification rate. When traffic waves are present, the average per-vehicle hydrocarbon emissions rate for Experiment I, J, and K, respectively are 0.003 g/mi, 0.003 g/mi, and 0.003 g/mi. When the AV is actively dampening the traffic flow, these are reduced by 51.6%, 38.7%, and 36.8% to 0.002 g/mi, 0.002 g/mi, and 0.002 g/mi, respectively. The carbon monoxide emissions in the presence of traffic waves are 0.503 g/mi, 0.491 g/mi, and 0.500 g/mi, for Experiment I, J, and K, respectively. When the AV is dampening the traffic waves, the carbon monoxide emissions are reduced by 39.3%, 36.2%, and 27.1% to 0.305 g/mi, 0.314 g/mi, and 0.364 g/mi, for Experiment I, J, and K, respectively. When a traffic wave is present, the average per-vehicle nitrogen oxide emissions...
emissions for Experiment I, J, and K are 0.006 g/mi, 0.005 g/mi, and 0.005 g/mi. These are reduced by 73.6%, 60.8%, and 63.4% to 0.002 g/mi, 0.002 g/mi, and 0.002 g/mi, for experiments A, B, and C, respectively, when the AV is actively dampening traffic waves. Finally, in when traffic waves are present the carbon dioxide emissions are 246.7 g/mi, 249.0 g/mi, and 245.0 g/mi, for Experiment I, J, and K, respectively. When the AV is actively dampening the traffic flow, the carbon dioxide emissions are reduced by 31.0%, 27.3% and 15.1% to 179.2 g/mi, 181.0 g/mi, and 208.0 g/mi, for Experiment I, J, and K, respectively.

The trend observed in Figures 6.5a through 6.5d is a decrease in per-vehicle emissions both when waves are present and when the AV is actively dampening the traffic waves. This reflects the anticipated stringent emissions requirements in the future. When considering Scenario 4 where the projected 2050 vehicle fleet with an assumed 80% EV market penetration rate is used for estimation, the reduction in average per-vehicle emissions rate has two sources: the increased efficiency of combustion engines and the electrification of the fleet, which in Scenario 4 assumes that 80% of the vehicles have zero tailpipe emissions. This is also true to a lesser extent in Scenario 3 where the 2030 vehicle fleet with a projected 3.4% EV penetration rate is assumed.

The experimental results for average per-vehicle emissions rates in Tables 6.3 through 6.5 are also represented graphically in Figure 6.5. These results show that in all three experiments (A, B, and C) the emissions rate in the presence of a wave is very similar. This indicates that in all three experiments, similar traffic conditions are obtained as seen in Figures 6.1 through 6.3. Furthermore, while the details of the specific controllers used in Experiment I, J, and K are different, they all have a similar effect on reducing the emissions rate in each of the thee experiments for each fleet scenario, indicating that there is a variety of possible controllers that may be able to achieve similar reductions in vehicle emissions.

When looking at the emissions reduction, we observe that the emissions reduction for each emissions category is approximately the same across the different scenar-
Experiment A (% reduction)  
Experiment B (% reduction)  
Experiment C (% reduction)  

<table>
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<th>Experiment B</th>
<th>Experiment C</th>
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<td>26.9 24.7 27.1 27.1</td>
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<td>27.2 27.5 27.3 27.3</td>
<td>14.8 15.5 15.1 15.1</td>
</tr>
</tbody>
</table>

Table 6.2: Percent reduction in emissions from period with waves to period when the AV is actively dampening the traffic.

<table>
<thead>
<tr>
<th>Type</th>
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<th>Scenario 2</th>
<th>Scenario 3</th>
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<td>W C R</td>
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<td></td>
<td>(g/mi)(g/mi)(%)</td>
<td>(g/mi)(g/mi)(%)</td>
<td>(g/mi)(g/mi)(%)</td>
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<td>2.984 1.812 39.3</td>
<td>0.503 0.305 39.3</td>
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<td>0.114 0.031 72.5</td>
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<td>1413 970.0 31.4</td>
<td>1019 703.0 31.0</td>
<td>246.7 179.2 31.0</td>
</tr>
</tbody>
</table>

Table 6.3: Experimental results from Experiment A for period with waves (W) and best control period (C) as identified in [13]. Reduction (R) is computed as difference between period with waves and period when the AV is actively dampening traffic waves and smoothing the traffic flow. Note that the percent reduction is computed based on the projected emissions, while the emissions rates are only presented to at most three decimal places in this table.

Thus, while the overall emissions are expected to reduce dramatically (Figures 6.5a through 6.5d), the impact that a low penetration rate of autonomous vehicles has on the traffic stream remains approximately unchanged.

Interestingly, as seen in Table 6.2, the percent reduction in NO\textsubscript{x} emissions is substantially greater than the percent reduction in other quantities across all scenarios and experiments. This is because high NOx emissions are highly correlated with transient engine behavior, while CO and CO\textsubscript{2} emissions are correlated more closely to the fuel burn rate [210].
(a) Hydrocarbon emissions rate for each experiment and fleet scenario considered showing both the emissions rate when waves are present and emissions rate when the traffic is under the control of the autonomous vehicle.

(b) Carbon monoxide emissions rate for each experiment and fleet scenario considered showing both the emissions rate when waves are present and emissions rate when the traffic is under the control of the autonomous vehicle.

(c) Nitrogen oxides emissions rate for each experiment and fleet scenario considered showing both the emissions rate when waves are present and emissions rate when the traffic is under the control of the autonomous vehicle.

(d) Carbon dioxide emissions rate for each experiment and fleet scenario considered showing both the emissions rate when waves are present and emissions rate when the traffic is under the control of the autonomous vehicle.

Figure 6.5: Emissions results for all four emissions categories from MOVES.
(a) Emissions reductions for all four fleet scenarios for Experiment I showing a generally consistent reduction in emissions for each emissions category across the four fleet scenarios considered.

(b) Emissions reductions for all four fleet scenarios for Experiment J showing a generally consistent reduction in emissions for each emissions category across the four fleet scenarios considered.

(c) Emissions reductions for all four fleet scenarios for Experiment K showing a generally consistent reduction in emissions for each emissions category across the four fleet scenarios considered.

Figure 6.6: Emissions reduction for each experiment by scenario. Lighter shaded bar represents the average per-vehicle emissions rate in the presence of traffic waves for a specific experiment while the darker bar represents the reduced average per-vehicle emissions rate when the AV is actively dampening the traffic.
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Table 6.4: Experimental results from Experiment B for period with waves (W) and best control period (C) as identified in [13]. Reduction (R) is computed as difference between period with waves and period when the AV is actively dampening traffic waves and smoothing the traffic flow. Note that the percent reduction is computed based on the projected emissions, while the emissions rates are only presented to at most three decimal places in this table.

<table>
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<th>Type</th>
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Table 6.5: Experimental results from Experiment C for period with waves (W) and best control period (C) as identified in [13]. Reduction (R) is computed as difference between period with waves and period when the AV is actively dampening traffic waves and smoothing the traffic flow. Note that the percent reduction is computed based on the projected emissions, while the emissions rates are only presented to at most three decimal places in this table.
6.4 Conclusions

The results presented in this chapter indicate that a single autonomous vehicle can have a substantial impact on reducing traffic emissions if properly controlled to dampen traffic waves and stabilize the traffic flow. While a single autonomous vehicle out of 22 vehicles is autonomous in the experiments presented in this chapter, this should be thought of as a uniform AV penetration rate of roughly 5%.

Putting these numbers into perspective, the impact that vehicle electrification has on the overall vehicle (tailpipe) emissions is roughly proportional to the number of combustion engine vehicles being replaced with electric vehicles. This is because, from a modelling perspective, EVs do not impact source emissions, and MOVES does not include power plant emissions to produce the electricity elsewhere. By replacing combustion engine vehicles with human-piloted electric vehicles, source polluters are being replaced with vehicles that have no tailpipe emissions but still contribute to congestion. Note that this does not include a possible increase in vehicle miles traveled by electric vehicles because of the perceived reduced environmental impact or decrease in costs that consumers may feel when driving electric vehicles [211].

Thus, when looking at pollutants such as NOx, replacing 5% of the vehicle fleet with properly-designed AVs has the same impact on emissions reduction as replacing roughly 75% of vehicles with electric vehicles. Importantly though, this only applies to driving conditions under which stop-and-go waves are present. This may only represent a small percentage of overall vehicle miles travelled by a typical driver. Therefore, it is unlikely that such significant reductions in emissions would be realized. However, there are additional benefits such as smoother driving and fewer braking events that come are realized, even with partial vehicle fleet automation [13]. Regardless, the findings of this chapter indicate that significant reductions in vehicle emissions may be possible if only a small number of vehicles on the road are replaced with more technologically-advanced vehicles.

While the overall per-vehicle emissions are expected to decrease over the next
several decades as vehicles are modernized and more stringent emissions standards are imposed, the impact that autonomous vehicles can have on reducing emissions remains relatively constant. This chapter finds that at a penetration rate of roughly 5%, AVs will be able to reduce hydrocarbon emissions by as much as 51.6%, carbon monoxide emissions by as much as 39.3%, nitrogen oxide emissions by as much as 73.6%, and carbon dioxide emissions by as much as 31.0% when comparing the smooth traffic under the control of AVs to the oscillatory traffic conditions observed with only human drivers. These AVs will enter our roadways in the near future regardless, so if properly designed to dampen traffic waves, this reduction in emissions comes at relatively little additional cost. Moreover, this reduction in emissions is not only realized by the AV, but manifested over the entire vehicle fleet, since all vehicles in the flow experience smoother driving behavior when the AV is actively dampening traffic waves.
7.1 Conclusions

This dissertation provides theoretical and experimental evidence for the impacts that a small number of vehicles with increased autonomous capabilities may have on traffic flow. The main contributions and findings are briefly summarized below:

- **Experimental work to demonstrate phantom traffic jams emerging from human driving behavior alone.** The experimental methodology and vehicle trajectory dataset developed as part of this dissertation (i) verify the results reported by Sugiyama, et al. [1] that human driving behavior alone is sufficient to cause phantom traffic jams to arise, and (ii) provide complete vehicle trajectory dataset to study the development of phantom traffic jams that goes beyond previous efforts by also including fuel consumption measurements.

- **Experimental and theoretical work to analyze the stability of commercially available ACC systems.** Experimental data is used to calibrate an ACC dynamical model for commercially-available ACC vehicles. The results indicate that current ACC vehicles are unstable and thus traffic jam amplifiers. However, simulation results with the calibrated model indicate that by increasing the headway of the ACC system, stability of the system
can be achieved, at the cost of throughput.

- **Stabilizing traffic flow with an autonomous vehicle.** While current ACC systems may be unstable, substantially more control of the traffic can be achieved with an autonomous vehicle. AV control algorithms are presented and tested on an AV in an experimental setting. The results presented in this dissertation indicate that a single AV, if properly controlled, can stabilize the traffic flow of up to 21 other vehicles in a single-lane of traffic. This has substantial implications on traffic throughput and fuel consumption. In the experiments conducted as part of this dissertation, throughput is increased by up to 14% and fuel consumption is decreased by as much as 39% when comparing the traffic conditions where stop-and-go waves are present to traffic conditions where the AV is actively dampening the traffic flow.

- **Emissions impact of AVs actively dampening traffic waves.** The potential benefits of AVs actively dampening traffic waves and stabilizing the traffic flow go beyond increases in throughput and a reduction in fuel consumption. Using the MOVES vehicle emissions model, the emissions under oscillatory traffic conditions in the presence of a phantom traffic jam are compared to the emissions when the AV is actively stabilizing the traffic stream. The results indicate that if properly controlled, AVs may be capable of reducing vehicle emissions by between 15% and 73% (depending on the type of pollutant) across the entire fleet at times when phantom jams are present. However such reductions in emissions will not be achieved in all driving circumstance but only at times when phantom jams would typically arise.

### 7.2 Limitations

The work presented in this dissertation provides first indications of the extent to which vehicles with increased autonomous capabilities are able to influence the traffic flow. This influence can have both positive and negative impacts on the traffic flow,
depending on how the automation is implemented. However, the dissertation is unable to address all aspects of how vehicle automation will impact traffic flow. Some limitations are listed below.

When it comes to modeling ACC systems, there is an inherent trade off between throughput and stability as seen in Chapter 2. By increasing the desired headway, we are able to drive the ACC system toward stability. However, this has the effect of increasing the spacing of vehicles on the roadway, which decreases throughput. For example, increasing the headway from 1.5 s to 3 s effectively reduces the throughput by 50%. While the increased stability may increase the throughput to some extent at the greater desired headway (findings from Chapter 5 indicate the increase throughput resulting from stabilized traffic flow is roughly 15%), it is unlikely that this increased throughput due to improvements in traffic stability will be sufficient to counteract the decrease in throughput resulting from the greater spacing.

Furthermore, the model used to describe ACC vehicle behavior is limited in its ability to capture the full range of ACC vehicle behavior. While this model is sufficient to understand the high-level ACC system behavior, there are certain aspects of ACC-vehicle behavior that cannot be captured with this model. For example, the model does not incorporate any delay within the system to account for processing and actuation time. Furthermore, the current ACC model does not account for different behavior under acceleration and braking. These are modelling simplifications that were made to understand the overall system behavior, but introduce modelling error.

Finally, considering control of traffic flow with a small number of AVs that are specifically controlled to dampen traffic waves, the proposed control has only been tested on single-lane roads, which may not be representative of an actual highway setting. This proof of concept shows that this type of control is possible, but does not address all challenges that must be resolved before such a system is ready for implementation.
7.3 Proposed future work

This dissertation developed four main contributions. However, some limitations exist as outlined in Section 7.2. Any future work in this direction should address these limitations. Specifically, future work should address the following items.

- The vehicle-level trajectory traffic data collected in the experiments described in Chapter 3 is limited since it observes traffic on a closed course. While this is beneficial for isolating external influences, more data in the style of the seminal NGSIM [57] must be collected from real highways. Continuous monitoring of a large section of highway would provide a very rich data source that could be used to better understand the development of phantom traffic jams, and to calibrate more accurate microscopic car following models.

- The ACC dynamical model used in this work is limited in that it may not be applicable at all speeds. Specifically, the model assumes a constant time headway. However, additional testing indicates that this may not always be a reasonable assumption. Further testing and model development is needed to construct more realistic ACC models that are able to incorporate a variable time headway to improve model fit. Additionally, it is apparent that some actuation delay exists on commercially-available vehicles. Therefore, extending the stability analysis to delay differential equations is an important step to better understand the stability of ACC systems.

- The experimental results presented in this dissertation that demonstrate the ability for a single AV to dampen traffic waves provide a valuable proof of concept, but several key improvements must be made before such a concept is viable for deployment on real highways. Specifically, the experiment presented is on a single lane track without merging or overtaking. This is not a realistic scenario, and further research is needed to address this limitation. Furthermore, additional research must be conducted to accurately and reliably
estimate the proper equilibrium velocity.

- The emissions results presented in this dissertation come from the MOVES model. While this model is well respected within the research community, future work should focus on obtaining a more accurate estimate of the impact of smoother driving on vehicle emissions by measuring the reductions with a portable emissions monitoring system. Furthermore, the limitations mentioned above in the previous bullet also apply for this work.
Bibliography


[189] H. Rakha, K. Ahn, and A. Trani. Comparison of mobile5a, mobile6, vt-


Appendix A: Appendix for Chapter 3

Data visualizations
Figure A.1: Visualization of Experiment A Data. Note that the color map fuel rate plot is capped at 6 l/h for enhanced visibility. A small fraction of measurements exceed 6 l/h, the maximum of which reaches 10.34 l/h. Black color indicates that no data are recorded.
Figure A.2: Visualization of Experiment B Data. Note that the color map fuel rate plot is capped at 6 l/h for enhanced visibility. A small fraction of measurements exceed 6 l/h, the maximum of which reaches 9.38 l/h. Black color indicates that no data are recorded.
Figure A.3: Visualization of Experiment C Data. Note that the color map fuel rate plot is capped at 6 l/h for enhanced visibility. A small fraction of measurements exceed 6 l/h, the maximum of which reaches 12.71 l/h. Black color indicates that no data are recorded.
Figure A.4: Visualization of Experiment D Data. Note that the color map fuel rate plot is capped at 6 l/h for enhanced visibility. A small fraction of measurements exceed 6 l/h, the maximum of which reaches 13.65 l/h. Black color indicates that no data are recorded.
Figure A.5: Visualization of Experiment E Data. Note that the color map fuel rate plot is capped at 6 l/h for enhanced visibility. A small fraction of measurements exceed 6 l/h, the maximum of which reaches 15.65 l/h. Black color indicates that no data are recorded.
Figure A.6: Visualization of Experiment F Data. Note that the color map fuel rate plot is capped at 6 l/h for enhanced visibility. A small fraction of measurements exceed 6 l/h, the maximum of which reaches 22.12 l/h. Black color indicates that no data are recorded.
Figure A.7: Visualization of Experiment G Data. Note that the color map fuel rate plot is capped at 6 l/h for enhanced visibility. A small fraction of measurements exceed 6 l/h, the maximum of which reaches 23.67 l/h. Black color indicates that no data are recorded.
Figure A.8: Visualization of Experiment H Data. Note that the color map fuel rate plot is capped at 6 l/h for enhanced visibility. A small fraction of measurements exceed 6 l/h, the maximum of which reaches 23.46 l/h. Black color indicates that no data are recorded.
Vehicle specifications

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Table A.1: Specifications of vehicles in the experiments.
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Table A.2: Vehicles used for each experiment. An × appears if a vehicle was used for a given experiment. Each vehicle has an unique driver throughout the experiments.
Appendix B: Appendix for Chapter 4

This appendix contains speed plots for all experiments presented in Chapter 4. First, the two-vehicle tests are presented, then the platoon test data are presented.

Figure B.1: Two-vehicle test data for Vehicle A with the minimum following setting.
Figure B.2: Two-vehicle test data for Vehicle A with the maximum following setting.
Figure B.3: Two-vehicle test data for Vehicle B with the maximum following setting.
Figure B.4: Two-vehicle test data for Vehicle C with the minimum following setting.
Figure B.5: Two-vehicle test data for Vehicle C with the maximum following setting.
Figure B.6: Two-vehicle test data for Vehicle D with the minimum following setting.
Figure B.7: Two-vehicle test data for Vehicle D with the maximum following setting.
Figure B.8: Two-vehicle test data for Vehicle E with the minimum following setting.
Figure B.9: Two-vehicle test data for Vehicle E with the maximum following setting.
Figure B.10: Two-vehicle test data for Vehicle F with the minimum following setting.
Figure B.11: Two-vehicle test data for Vehicle F with the maximum following setting.
Figure B.12: Two-vehicle test data for Vehicle G with the minimum following setting.
Figure B.13: Two-vehicle test data for Vehicle G with the maximum following setting.
Figure B.14: Platoon data for test 1.

Figure B.15: Platoon data for test 2.
Figure B.16: Platoon data for test 2.

Figure B.17: Platoon data for test 4.
Figure B.18: Platoon data for test 7.

Figure B.19: Platoon data for test 8.
Figure B.20: Platoon data for test 9.

Figure B.21: Platoon data for test 10.
Figure B.22: Platoon data for test 11.

Figure B.23: Platoon data for test 12.