Transportation Research Part D 67 (2019) 351–365

Contents lists available at ScienceDirect

Transportation Research Part D

journal homepage: www.elsevier.com/locate/trd

Quantifying air quality benefits resulting from few autonomous vehicles stabilizing traffic

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ARTICLE INFO

Keywords:
Vehicle emissions
Traffic waves
Autonomous vehicles
Traffic stability

ABSTRACT

It is anticipated that in the near future, the penetration rate of vehicles with some autonomous capabilities (e.g., adaptive cruise control, lane following, full automation, etc.) will increase on roadways. This work investigates the potential reduction of vehicular emissions caused by the whole traffic stream, when a small number of autonomous vehicles (e.g., 5% of the vehicle fleet) are designed to stabilize the traffic flow and dampen stop-and-go waves. To demonstrate this, vehicle velocity and acceleration data are collected from a series of field experiments that use a single autonomous-capable vehicle to dampen traffic waves on a circular ring road with 20–21 human-piloted vehicles. From the experimental data, vehicle emissions (hydrocarbons, carbon monoxide, carbon dioxide, and nitrogen oxides) are estimated using the MOVES emissions model. This work finds that vehicle emissions of the entire fleet may be reduced by between 15% (for carbon dioxide) and 73% (for nitrogen oxides) when stop-and-go waves are reduced or eliminated by the dampening action of the autonomous vehicle in the flow of human drivers. This is possible if a small fraction (~5%) of vehicles are autonomous and designed to actively dampen traffic waves. However, these reductions in emissions apply to driving conditions under which stop-and-go waves are present. Less significant reductions in emissions may be realized from a deployment of AVs in a broader range of traffic conditions.

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

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https://doi.org/10.1016/j.trd.2018.12.008

Available online 14 December 2018
1361-9209/

compared to entirely human-piloted traffic (Stern et al., 2018). Smooth driving profiles result in lower fuel consumption and emissions, which are damaging to the environment and to human health (Dockery et al., 1993).

The main focus of this article 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 data collected during a series of experiments in which a single autonomous vehicle is carefully controlled to dampen stop-and-go waves that arise when human-piloted traffic is sufficiently dense (Stern et al., 2018). The data used to assess the potential emissions impact of AVs stabilizing the traffic flow is found in the work by Stern et al. (2018). The primary contribution of the work by Stern et al. (2018) was the design of controllers to dampen traffic waves.

The reduction in emissions of the total traffic flow are estimated from the experimental data using the *MOtor Vehicle Emissions Model* (MOVES) (Environmental Protection Agency, 2015). While the introduction of AVs at large penetration rates is certain to induce large effects such as changes in land use (Kockelman et al., 2017), travel demand (Harb et al., 2018), mode choice (LaMondia et al., 2016), and vehicle ownership (Fagnant and Kockelman, 2015), 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., between 15% and 73% depending on the pollutant). To the best of our knowledge, this is the first of its kind study to use experimental data to demonstrate that that even at a low market penetration rate, the presence of AVs in the traffic flow may have the potential to reduce vehicle emissions of the overall traffic flow.

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 (Chapman, 2007). These emissions are made worse by congestion and stop-and-go traffic (Barth and Boriboonsomsin, 2008). Recently, a broad range of efforts have been made to curb vehicle emissions (Shaheen and Lipman, 2007). These efforts include vehicle improvements to increase the efficiency of combustion engines (Reitz and Duraisamy, 2015; Schäfer and Van Basshuysen, 2013) and a transition to hybrid vehicles (Fontaras et al., 2008; De Haan et al., 2007). It also includes traffic network management strategies that have focused on more efficient vehicle routing and traffic control (Boriboonsomsin et al., 2012; Vreeswijk et al., 2010; Yang et al., 2017). It is anticipated that AVs will also impact vehicle emissions, though it is unclear whether they will increase or decrease overall traffic emissions (Chen et al., 2017; Stephens et al., 2016).

Direct measurement of vehicle emissions has been an area of intense research interest for several decades (Frey et al., 2003; Harrington, 1997; Schuetzle, 1983; Tong et al., 2000). However, due to the large cost associated with emissions measurement equipment, there has been a significant push (An et al., 1997; Rakha et al., 2004; Rakha et al., 2003) 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 (Environmental Protection Agency, 2015) and MOBILE6 (Environmental Protection Agency, 2003) as well as the *European Environment Agency* COPERT (Kouridis et al., 2000) and ARTEMIS (André et al., 2009) 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 (An et al., 1997), EMIT (Cappiello et al., 2002), POLY (Teng et al., 2002), and VT-Micro (Ahn et al., 2002, Rakha et al. (2003), Rakha et al. (2004)). These models are typically used for estimating emissions of individual vehicles under some specified *drive cycle* or test procedure.

The MOVES model offers both an aggregate analysis as discussed above as well as a *vehicle-specific power* (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 (1 Hz), 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 examples, see the works by Alam et al. (2014), Wang et al. (2016), Xu et al. (2016), Zhao and Sadek (2013). 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 article relies on emissions estimates from a VSP analysis conducted in MOVES.

1.2. Related work on human-generated traffic waves and wave dampening

Traffic waves are a common phenomenon on urban highways. They have been shown to arise even in the absence of external bottlenecks such as merges or reduction in lanes. This has been experimentally demonstrated by Sugiyama et al. (2008), where 22 vehicles drive on a ring-road track as well as by Tadaki et al. (2013), who conduct similar experiments with between 10 and 40 vehicles. In both cases the vehicles begin with uniform speed and spacing, but the flow quickly devolves into a stop-and-go wave that travels upstream. These results have been independently validated in the experiments of Stern et al. (2018) and Wu et al. (2017), which replicated the Sugiyama et al. (2008) experimental design, and confirmed that human driving behavior alone is sufficient to trigger traffic instabilities such as stop-and-go waves. These traffic instabilities are often referred to as *phantom jams* (Kerner and Konhäuser, 1993) and can reduce the throughput and increase the fuel consumption of all vehicles on the roadway (Stern et al., 2018).

The ability of AVs to reduce emissions has been considered by several simulation-based works reviewed below (Liu et al., 2017; Yang and Jin, 2014). Liu et al. (2017) 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. (2017) do not consider field data captured from vehicles. Moreover, they only considers the direct benefits of a smooth driving profile on the emissions of the AV, and do not capture the potential of AVs to also reduce the emissions of human piloted vehicles due to the smoother driving profile the AVs that may propagate to human drivers.

Yang and Jin (2014) 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 article, the simulation results of Yang and Jin (2014) 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. Servin et al. (2006) study the use of 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. Servin et al. (2006) 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.

1.3. Contribution and outline

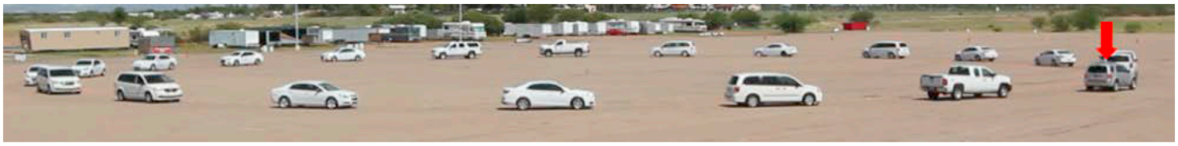
The works discussed above provide simulation results to give insight into the possible reduction in emissions that may result from even just a small portion of the vehicle fleet becoming autonomous. In contrast, this article uses experimental data from Stern et al. (2018), to analyze the impact of a 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. While the experimental data used for this study consider a uniform AV penetration rate of roughly 5%, higher AV penetration rates will likely be required for deployments of such systems on real freeways.

This article 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 conducted by Stern et al. (2018) on a circular ring road similar those of Sugiyama et al. (2008), and estimating the microscopic vehicle emissions using the VSP analysis in MOVES. The use of the ring road is experimentally beneficial since it allows for the isolation of car following behavior alone, without capturing confounding factors such as lane changing. 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 article. 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 1.

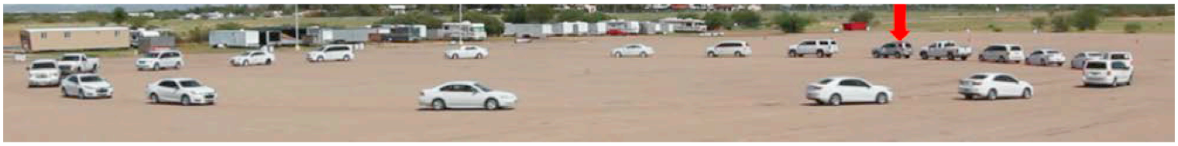
Table 1

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.

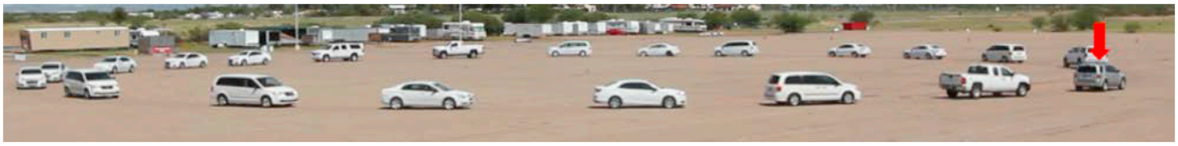
Scenario	Electric vehicle fraction (%)	Sedan fraction (%)	Small truck fraction (%)
1	0.0	45.5	54.5
2	0.0	51.2	48.8
3	3.4	44.5	55.6
4	80.0	42.8	57.2



(a) Alignment of vehicles at start of Experiment A.



(b) Alignment of vehicles 95 seconds into Experiment A when wave is present in back right.



(c) Alignment of vehicles 328 seconds into Experiment A when the CAT Vehicle is actively dampening the wave.

Fig. 1. Experimental track with 21 vehicles during Experiment A. The position of the CAT Vehicle is shown with a red arrow. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

This work is part of a larger body of research that explores how traffic waves develop and the impacts of a small number of AVs actively dampening the traffic flow. This includes an article that presents a dataset with vehicle trajectories and a data collection methodology by (Wu et al., 2017) as well as work on the traffic flow implications of AVs Stern et al. (2018). 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 20–21 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 between 15% and 73%. The remainder of the article is organized as follows. We first 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 2. The results are presented in Section 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 4.

2. Methodology

In this section, the methodology used in the experimental design and execution, as well as data analysis is discussed. 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.

2.1. Experimental setup

The vehicle trajectories used to estimate vehicle emissions in this article are obtained from the experiments described in Stern et al. (2018). The experiments consist of between 21 and 22 vehicles driving on a single lane ring track, 82.8 m in diameter (260 m track length), located in a large parking lot in Tucson, AZ as seen in Fig. 1. The experiments are designed to have a similar vehicle density as the experiment conducted by Sugiyama et al. (2008).

Vehicles are obtained from the University of Arizona motor pool, and are all recent model year passenger vehicles. 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 min, with breaks between to reset the track and allow for drivers to rest.

A single vehicle in the experiment, the University of Arizona's *Cognitive and Autonomous Test* (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 A and C), or by instructing the driver of the CAT Vehicle to drive with a specific velocity (Experiment B). 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. A brief overview of the experimental procedure is presented below.

1. Set vehicles on track at starting positions (even spacing)
2. Begin driving, all vehicles under human control
3. Intervene by instructing driver of CAT Vehicle to engage AV mode (Experiment A and C) or change driving behavior (Experiment B)
4. End experiment, all vehicles come to rest

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. The full data are provided by Stern et al. (2018), and details of the algorithms used to process the data are provided by Wu et al. (2017).

2.2. Dampening traffic waves

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* (Cui et al., 2017) 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. While the equilibrium velocity may depend on a number of factors, practically, the local average speed may be used as a good approximation of the equilibrium velocity. 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 and a detailed explanation of the controllers used on the CAT Vehicle to dampen traffic waves is provided by Stern et al. (2018).

2.2.1. 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 Stern et al. (2018).

2.2.2. 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.

2.2.3. 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 (Åström and Murray, 2008). 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.

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. We adopt MOVES since 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 in 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 2.4) or based on fleet mix projections (Scenarios 2–4) as discussed in Section 2.4.
4. Vehicle fleet age distribution: Emissions of vehicles vary based on age of vehicles due to an effect known as emissions deterioration (Zachariadis et al., 2001). 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.
5. VSP Distribution: For each experiment, the instantaneous velocity and acceleration is obtained from the experiments by Stern et al. (2018). 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 (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.

$$\text{VSP} \approx \phi_1 va + \phi_2 v + \phi_3 v^3, \tag{1}$$

where $\phi_1 = 0.22$, $\phi_2 = 0.0954$, $\phi_3 = 0.0000272$ (Jimenez et al., 1999). Using this approximation for all vehicles neglects small differences in air resistance due to vehicle form or rolling resistance due to tire pressure.

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 use the same experimentally-collected vehicle trajectories for all scenarios and represent different vehicle fleet mixes as described below. These scenarios are detailed in Table 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 (US Energy Information Administration, 2017). 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.

3. Experimental results

For completeness we briefly describe the three traffic experiments that are conducted. A full description of the experimental setup is provided in Section 2. The goal of the experiments is to demonstrate the ability of a single AV to dampen traffic waves that naturally occur from human driving behavior. A total of three wave-dampening strategies are used in the three ring road experiments.

The vehicles can be seen on the track at various stages in the experiment in Fig. 1. Specifically, in Fig. 1a, the vehicles are observed with uniform spacing at the start of the experiment. After 95 s, a stop-and-go wave is present in the traffic flow and the configuration of vehicles on the ring road is seen in Fig. 1b. Finally, when the AV is actively dampening the traffic flow, the uniform traffic flow 328 s after the start of the experiment is seen in Fig. 1c.

In Experiment A, the FollowerStopper controller is used to dampen traffic waves, while in Experiment B a human driver is instructed to drive the CAT Vehicle at a constant speed, and in Experiment C 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 Figs. 2–4 for Experiments A, B, and C, respectively. Summary statistics of each experiment are provided in Table 2.

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

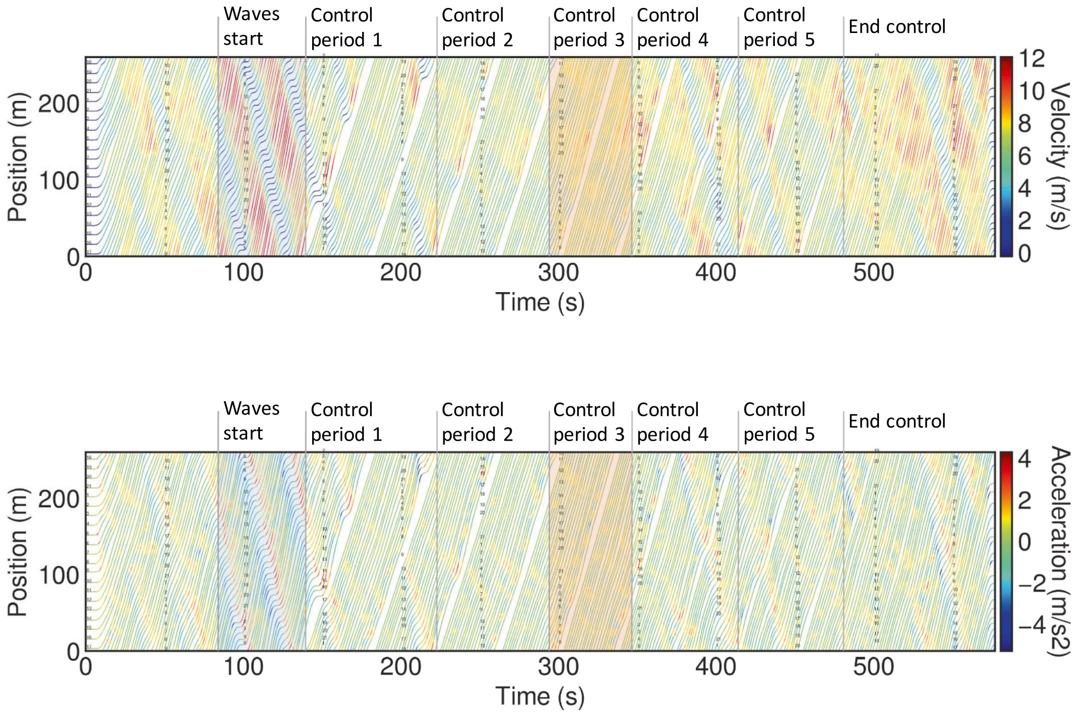


Fig. 2. Vehicle trajectories for all vehicles in Experiment A color coded by, velocity (top), and acceleration (bottom). The time under which traffic waves are present is shaded blue, while the control period used for analysis, where the AV is actively dampening traffic waves is shaded red. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

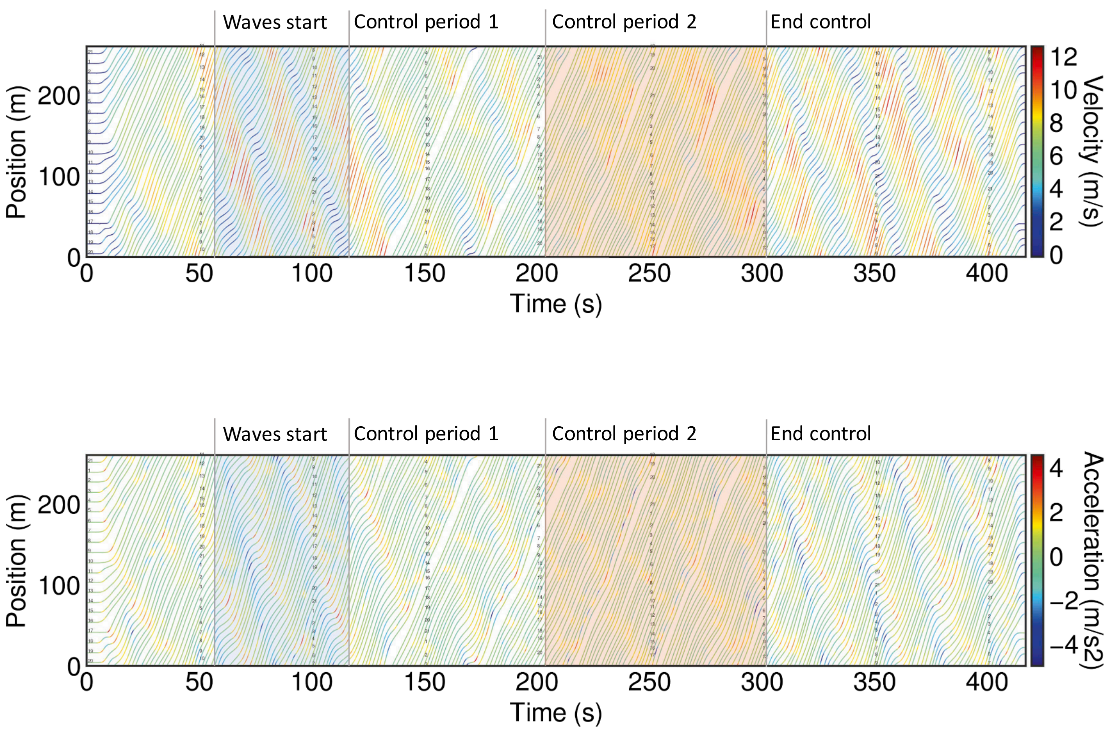


Fig. 3. Vehicle trajectories for all vehicles in Experiment B color coded by, velocity (top), and acceleration (bottom). The time under which traffic waves are present is shaded blue, while the control period used for analysis, where the AV is actively dampening traffic waves is shaded red. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

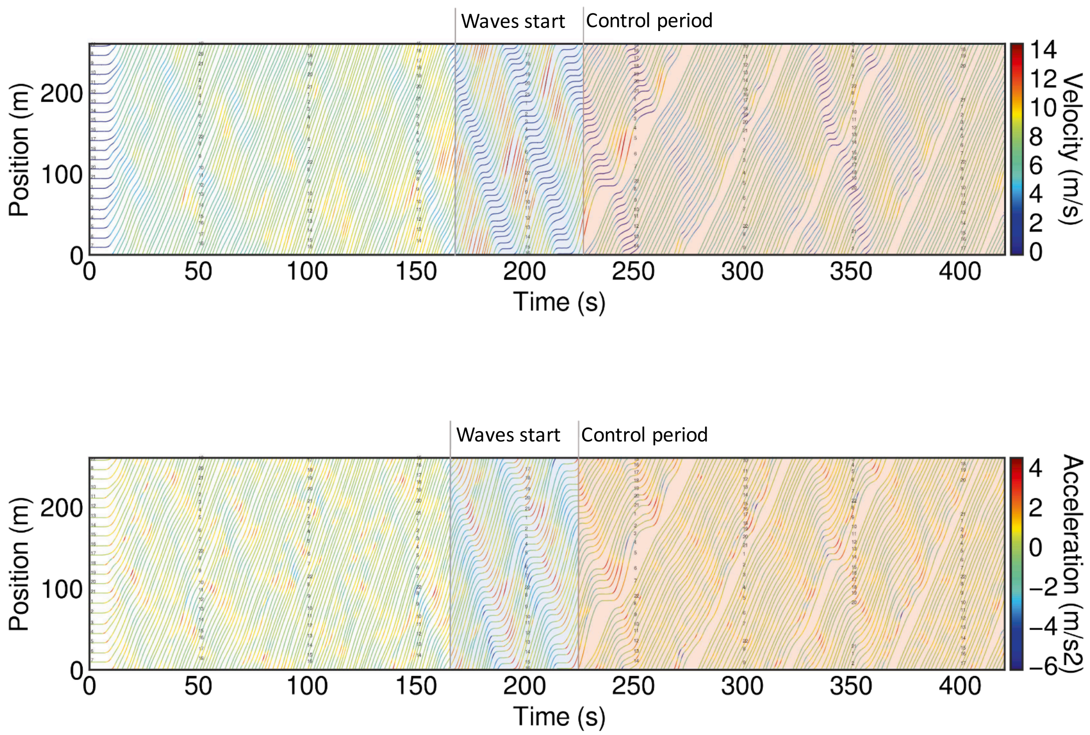


Fig. 4. Vehicle trajectories for all vehicles in Experiment C color coded by, velocity (top), and acceleration (bottom). The time under which traffic waves are present is shaded blue, while the control period used for analysis, where the AV is actively dampening traffic waves is shaded red. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Table 2
Experiment summary statistics.

Experiment	Total time (s)	Avg. speed no control (m/s)	Avg. speed with control (m/s)
A	567	6.33	7.04
B	409	6.29	6.86
C	413	6.05	5.57

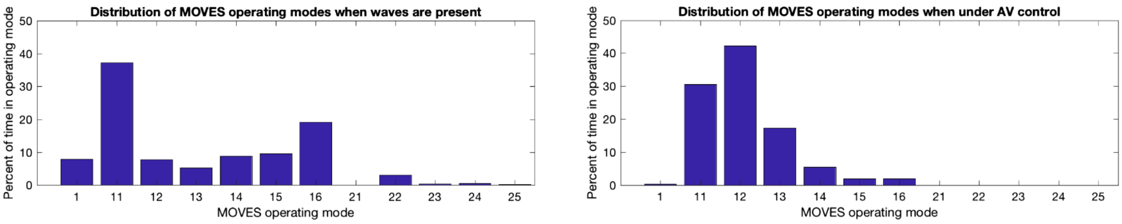
the purposes of this analysis only the period when waves are present and the period where the AV controller is most effective are used.

3.1. MOVES operating mode distribution

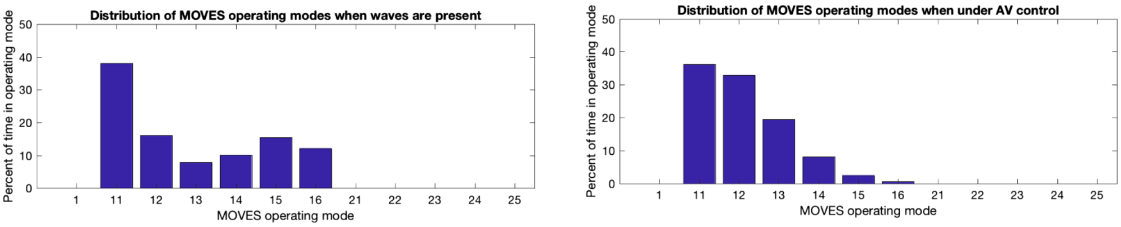
The MOVES analysis is based on the percentage of time in each drive schedule that is spent in a particular *operating mode*. These operating modes are specified by defining specific ranges of speed and VSP. Consequently, it is possible to classify each moment of the drive schedule as one of a number 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 (Environmental Protection Agency, 2015).

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 Fig. 5a–c. 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.

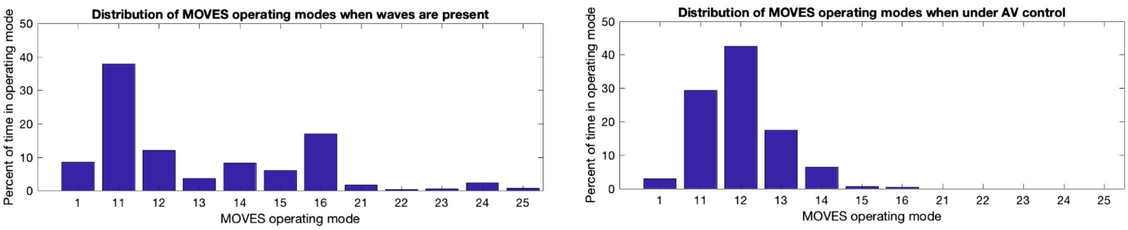
As seen in Fig. 5a–c, when comparing the MOVES operating mode distribution under uncontrolled conditions when traffic waves are present (left) to the operating mode distribution when the CAT Vehicle is actively dampening the traffic flow (right), the operating mode distribution shifts from higher operating 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. Note that these distributions do not change under the scenarios considered.



(a) Distribution of MOVES operating modes in Experiment A.



(b) Distribution of MOVES operating modes in Experiment B.



(c) Distribution of MOVES operating modes in Experiment C.

Fig. 5. 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). 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. Additionally, note that these distributions are applicable to all scenarios.

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 A, 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 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 B, 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 C, 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. The results can also be seen in Tables 3–6.

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 A in the presence of

Table 3
Percent reduction in emissions from period with waves to period when the AV is actively dampening the traffic.

	Experiment A (% reduction)				Experiment B (% reduction)				Experiment C (% reduction)			
Scenario:	1	2	3	4	1	2	3	4	1	2	3	4
HC	51.5	38.4	50.4	51.6	38.7	28.0	37.8	38.7	36.8	17.8	35.1	36.8
CO	39.1	38.1	39.3	39.3	36.1	34.6	36.1	36.1	26.9	24.7	27.1	27.1
NO_x	73.5	64.0	72.5	73.6	60.8	52.9	59.8	60.8	63.3	52.0	61.9	63.4
CO_2	30.7	31.4	31.0	31.0	27.2	27.5	27.3	27.3	14.8	15.5	15.1	15.1

Table 4
Experimental results from Experiment A for period with waves (W) and best control period (C) as identified in Stern et al. (2018). 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.

	Scenario 1			Scenario 2			Scenario 3			Scenario 4		
Pollutant	W (g/mi)	C (g/mi)	R (%)	W (g/mi)	C (g/mi)	R (%)	W (g/mi)	C (g/mi)	R (%)	W (g/mi)	C (g/mi)	R (%)
HC	0.010	0.005	51.5	0.191	0.125	38.4	0.019	0.010	50.4	0.003	0.002	51.6
CO	2.430	1.481	39.1	7.843	4.854	38.1	2.984	1.812	39.3	0.503	0.305	39.3
NO_x	0.107	0.028	73.5	0.933	0.336	64.0	0.114	0.031	72.5	0.006	0.002	73.6
CO_2	1246	863.1	30.7	1413	970.0	31.4	1019	703.0	31.0	246.7	179.2	31.0

Table 5
Experimental results from Experiment B for period with waves (W) and best control period (C) as identified in Stern et al. (2018). 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.

	Scenario 1			Scenario 2			Scenario 3			Scenario 4		
Pollutant	W (g/mi)	C (g/mi)	R (%)	W (g/mi)	C (g/mi)	R (%)	W (g/mi)	C (g/mi)	R (%)	W (g/mi)	C (g/mi)	R (%)
HC	0.010	0.006	38.7	0.189	0.136	28.0	0.018	0.011	37.8	0.003	0.002	38.7
CO	2.380	1.520	36.1	7.740	5.060	34.6	2.920	1.860	36.1	0.491	0.314	36.2
NO_x	0.095	0.037	60.8	0.872	0.411	52.9	0.101	0.041	59.8	0.005	0.002	60.8
CO_2	1260	916.0	27.2	1420	1030	27.5	1030	748.0	27.3	249.0	181.0	27.3

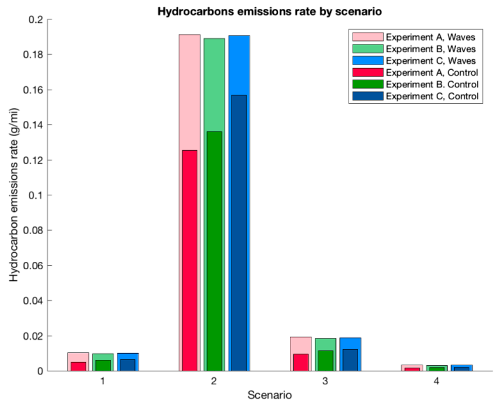
Table 6
Experimental results from Experiment C for period with waves (W) and best control period (C) as identified in Stern et al. (2018). Reduction (R) is computed as difference between period with waves and period when the AV is actively dampening traffic waves and smoothing the traffic flow. Note 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.

	Scenario 1			Scenario 2			Scenario 3			Scenario 4		
Pollutant	W (g/mi)	C (g/mi)	R (%)	W (g/mi)	C (g/mi)	R (%)	W (g/mi)	C (g/mi)	R (%)	W (g/mi)	C (g/mi)	R (%)
HC	0.010	0.006	36.8	0.191	0.157	17.8	0.019	0.012	35.1	0.003	0.002	36.8
CO	2.420	1.770	26.9	7.760	5.840	24.7	2.960	2.160	27.1	0.500	0.364	27.1
NO_x	0.101	0.037	63.3	0.884	0.424	52.0	0.107	0.041	61.9	0.006	0.002	63.4
CO_2	1240	1060	14.8	1410	1190	15.5	1010	861.0	15.1	245.0	208.0	15.1

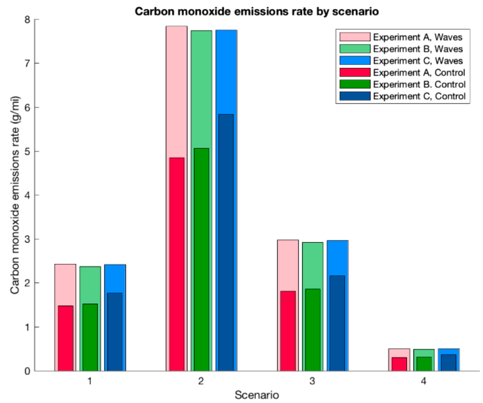
traffic waves are 0.191 g/mi HC, 7.843 g/mi CO, 0.933 g/mi NO_x, and 1413 g/mi CO2. When the AV is actively dampening the traffic flow, the HC emissions are reduced by 38.4% to 0.125 g/mi, the CO emissions are reduced by 38.1% to 4.854 g/mi, the NO_x emissions are reduced by 64% to 0.336 g/mi, and the CO2 emissions are reduced by 31.4% to 970 g/mi.

In Experiment B, 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 dioxide 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.

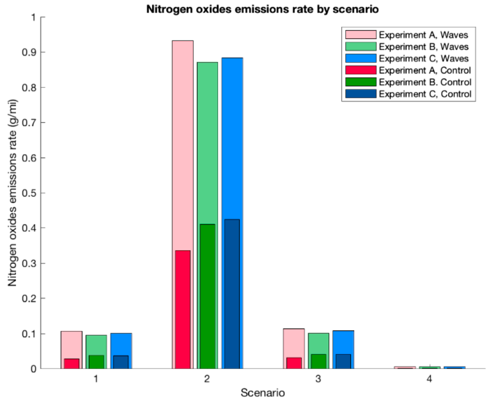
In Experiment C, when traffic waves are present the average per-vehicle hydrocarbon emissions are 0.191 g/mi, the carbon



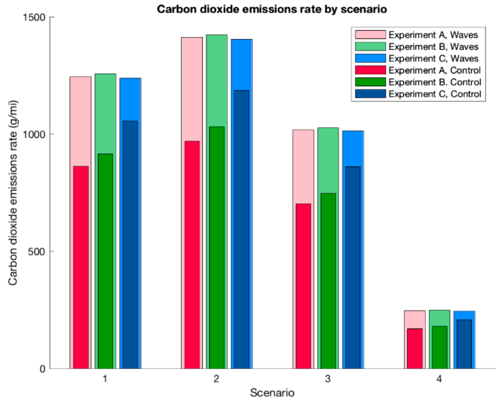
(a) Hydrocarbon emissions rate.



(b) Carbon monoxide emissions rate.



(c) Nitrogen oxides emissions rate.



(d) Carbon dioxide emissions rate.

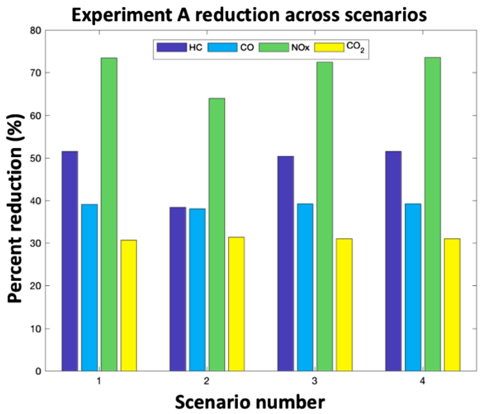
Fig. 6. Emissions results for all four emissions categories for each experiment and fleet scenario considered showing both the emissions rate when waves are present and emissions rate when the traffic is under the control of the autonomous vehicle.

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. The results can also be seen in Tables 3–6.

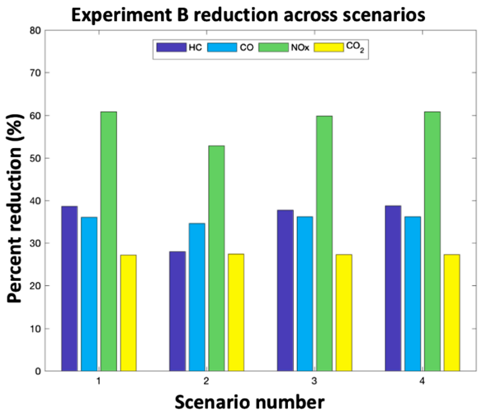
Fig. 6a–d show that the hydrocarbon, carbon monoxide, and nitrogen oxide emissions for Scenario 2 are substantially higher than in Scenario 1. This is because the vehicle fleet used in Scenario 1 was mostly 2016 and 2015 model year vehicles (full details on the vehicles used can be found in Stern et al. (2018)) 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. (see Fig. 7).

3.4. Scenarios 3 and 4: Emissions of projected future fleets

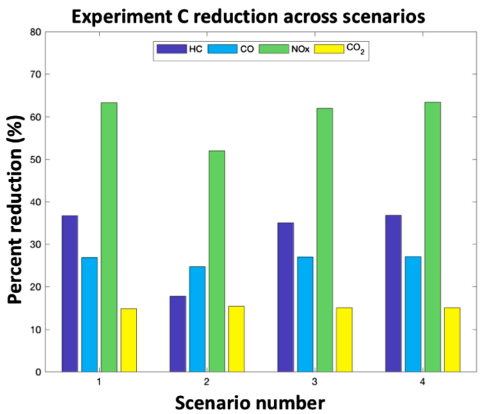
The projected future vehicle fleet scenarios presented in Table 1 are also considered. The emissions for these scenarios are presented below. In Scenario 3, the projected 2030 US vehicle fleet us used for estimation. In Experiment A, B, and C the hydrocarbon emissions in the presence of traffic waves 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 Experiments A, B, and C 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 Experiments A, B, and C, 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 Experiments A, B, and C, respectively. In the presence of a traffic wave, the nitrogen oxide emissions for Experiments A, B, and C 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 Experiments A, B, and C by 72.5%, 59.8%, and 61.0% to 0.031 g/mi, 0.041 g/mi, and 0.041 g/mi, respectively.



(a) Emissions reductions for all four fleet scenarios for Experiment A.



(b) Emissions reductions for all four fleet scenarios for Experiment B.



(c) Emissions reductions for all four fleet scenarios for Experiment C.

Fig. 7. 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. Note the generally consistent reduction in emissions for each emissions category across the four fleet scenarios considered.

Finally, when traffic waves are present, the average per-vehicle emissions of carbon dioxide for Experiments A, B, and C 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 Experiments A, B, and C, 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 Experiments A, B, and C, 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 Experiments A, B, and C, respectively. When a traffic wave is present, the average per-vehicle nitrogen oxide emissions for Experiments A, B, and C 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 Experiments A, B, and C, 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 Experiments A, B, and C, respectively. The results for Scenarios 3 and 4 can also be seen in Tables 3–6.

The trend observed in Fig. 6a–d 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 4–6 are also represented graphically in Fig. 6. 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 observed as seen in Figs. 2–4. Furthermore, while the details of the specific controllers used in Experiments A, B, and C 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 caused by stop-and-go traffic.

When looking at the emissions reduction, we observe that the emissions reduction for each emissions category is approximately the same across the different scenarios for each experiment. Thus, while the overall emissions are expected to reduce dramatically (Fig. 6a–d), the impact that a low penetration rate of autonomous vehicles has on the traffic stream remains approximately unchanged.

Interestingly, as seen in Table 3, the percent reduction in NO_x emissions is substantially greater than the percent reduction in other quantities across all scenarios and experiments. This is because high NO_x emissions are correlated with transient engine behavior, while CO and CO_2 emissions are correlated more closely to the fuel burn rate (Mei et al., 2016).

4. Conclusions

The results presented in this article 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 article, this should be thought of as a uniform AV penetration rate of roughly 5%. These results represent the reduction in vehicle emissions that is possible due to the smoother traffic flow that may result from AVs dampening traffic waves, and the impact this has on the underlying traffic dynamics. These results are based on experimental data that is collected in a controlled environment to isolate the wave-amplifying car following behavior of human drivers in the absence of lane changing or other external factors.

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 (Font Vivanco et al., 2014).

Thus, when looking at pollutants such as NO_x, 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 work is limited in that it considers the emissions during stop-and-go traffic waves. These traffic waves are a common phenomenon in urban highway traffic but 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 across an entire drive. However, there are additional benefits such as smoother driving and fewer braking events that are realized, even with partial vehicle fleet automation (Stern et al., 2018). Additionally, the experiment was limited to a single AV and a limited track size. Therefore, only a small range of AV penetration rates could be experimentally tested. Regardless, the findings of this article 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.

A limitation of the experimental setup used in this article is that there is only one lane of traffic, which is not typical for highway settings. However, importantly, the types of instabilities observed in this experimental setting are the same types of instabilities often observed on highways. Factors such as lane changing and merging, which are present on highways, may make it more difficult for an AV to dampen traffic waves. However, since the instabilities are the same types of instabilities observed in this experimental setting, the experimental results obtained in this experiment are applicable, though a higher AV penetration rate may ultimately be required to obtain the same reductions in emissions observed in this article.

Generally speaking, the FollowerStopper controller (Experiment A) is the most effective controller since it is able to reduce the vehicle emissions the most. This finding is consistent with the results reported by Stern et al. (2018) where the FollowerStopper controller was able to achieve the greatest reduction in velocity standard deviation.

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 article 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.

Acknowledgements

This material is based upon work supported by the National Science Foundation under Grants No. CNS-1446715 (Piccoli), CNS-1446690 (Seibold), CNS-1446435 (Sprinkle), and CNS-1446702 (Work) as well as the Federal Highway Administration under Grant No. 693JJ31845050. This research was also supported by the Inria associated team “ModEling autonoMous vEhicles iN Traffic flOw (MEMENTO)”.

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