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Fuel economy testing of autonomous vehicles

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ABSTRACT

Environmental pollution and energy use in the light-duty transportation sector are currently regulated through fuel economy and emissions standards, which typically assess quantity of pollutants emitted and volume of fuel used per distance driven. In the United States, fuel economy testing consists of a vehicle on a treadmill, while a trained driver follows a fixed drive cycle. By design, the current standardized fuel economy testing system neglects differences in how individuals drive their vehicles on the road. As autonomous vehicle (AV) technology is introduced, more aspects of driving are shifted into functions of decisions made by the vehicle, rather than the human driver. Yet the current fuel economy testing procedure does not have a mechanism to evaluate the impacts of AV technology on fuel economy ratings, and subsequent regulations such as Corporate Average Fuel Economy targets. This paper develops a method to incorporate the impacts of AV technology within the bounds of current fuel economy test, and simulates a range of automated following drive cycles to estimate changes in fuel economy. The results show that AV following algorithms designed without considering efficiency can degrade fuel economy by up to 3%, while efficiency-focused control strategies may equal or slightly exceed the existing EPA fuel economy test results, by up to 10%. This suggests the need for a new near-term approach in fuel economy testing to account for connected and autonomous vehicles. As AV technology improves and adoption increases in the future, a further reimagining of drive cycles and testing is required.

1. Introduction

Management of environmental pollution and energy use in the light-duty transportation sector is currently regulated through fuel economy and emissions standards. In the United States (U.S.), Japan, and the European Union these standards are in the form of quantity of pollutants emitted and volume of fuel used per distance driven (Atabani et al., 2011). Compliance with these standards is evaluated via a standardized fuel economy and emissions test. The U.S. test consists of a vehicle on a treadmill, while a trained driver follows a fixed velocity schedule, or drive cycle (EPA, n.d. A). During the test all effluent from the tailpipe is tested for pollutant levels, and carbon dioxide levels are used to estimate fuel usage (EPA, n.d. A). This is done for five different types of drive cycles, to simulate different conditions (EPA, n.d. B). The results from each test are then aggregated to ascertain if the vehicle is complying with emissions standards. In addition, the tests are weighted four separate ways to determine fuel efficiency with respect to required standards and reporting to the consumer in the form of highway, city, and combined fuel efficiency (EPA, n.d. B). This system allows for a standardized method to compare all passenger vehicles in the U.S. market, streamlining the regulatory process.

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By design, the current standardized fuel economy testing system neglects differences in how individuals actually drive their vehicles on the road. As autonomous vehicle (AV) technology is introduced, more aspects of driving are shifted into functions of decisions made by the vehicle, rather than the human driver. Yet the current fuel economy testing procedure does not have a direct mechanism to evaluate the impacts of AV technology on fuel economy ratings. Autonomous and partially autonomous vehicle technology has advanced greatly over the past several years, with adaptive cruise control (ACC) with lane assist systems already reaching the market, and more advanced technologies have been announced for the coming years. While these systems may allow vehicle manufacturers to optimize their partially-autonomous vehicle control systems for fuel efficiency, these systems will not affect vehicle fuel economy ratings unless they are included in fuel economy testing. Hence, manufacturer incentives will not be aligned with improving fuel economy. Without inclusion into fuel economy ratings, autonomous technology will not help manufacturers meet their required Corporate Average Fuel Economy (CAFE) targets and manufacturers cannot advertise the increased vehicle fuel efficiency. Under such incentives, manufacturers are likely to make vehicle control decisions that increase vehicle desirability at the cost of fuel efficiency. Currently, the National Transportation Safety Board is considering if certain partially-autonomous technologies should be included as standard vehicle features for safety reasons (Mlot, 2015). Requiring autonomous technologies on new vehicles for safety reasons would enhance the importance of understanding their impacts on vehicle fuel economy.

The EPA has addressed similar issues of emerging technologies through "off-cycle technology credits" for CAFE standards, and is likely to continue this practice for autonomous technology (EPA and NHTSA, 2010). A manufacturer may petition for an increase in a vehicle's CAFE fuel economy rating if it can demonstrate the current two-cycle test does not capture some fuel efficiency gains that "new and innovative technologies" provide (EPA and NHTSA, 2010). There are three potential challenges if this approach is used for autonomous vehicle technology. First, off-cycle technology credits only apply to new and non-standard technologies. Once other manufacturers begin to adopt them, as has already happened for many early autonomous features, they are no longer eligible. Second, the process is non-standardized. A manufacturer must submit a testing and validation method, which has to be granted preliminary approval, and go through a public review process. In addition, the EPA will not certify the method or results (EPA and NHTSA, 2010), meaning that these technologies may not be tested equivalently across manufacturers. The final challenge is that this will only apply for CAFE standards and not fuel economy ratings that inform the consumer (EPA and NHTSA, 2010). Hence a manufacturer still cannot reflect the impacts of this technology in its fuel economy stickers and may face restrictions when trying to advertise any fuel economy benefits to consumers.

As autonomous vehicle technologies become more prevalent, the current drive cycle system should be expanded to include drive cycles for autonomous and partially autonomous vehicles. This paper makes a contribution to the literature by demonstrating a method to incorporate autonomous following drive cycles into the existing EPA testing regimen. This method was developed primarily for near-term conditions, where the majority of traffic is comprised of conventionally-driven vehicles. This method would allow the current dynamometer testing to continue, while accounting for the introduction of AV technologies. This approach was tested on a range of possible drive behaviors, modeling different priorities that a vehicle manufacturer may wish to pursue to obtain new testing drive cycles. The fuel consumption resulting from these drive cycles were then simulated on a variety of vehicles using the Virginia Tech Comprehensive Fuel Consumption Model (Edwardes and Rakha, 2014; Park et al., 2013; Rakha et al., 2011; Saerens et al., 2013), and then compared. While the ultimate procedure adopted by EPA will have to comply with regulatory requirements, the methods outlined here demonstrate the need for a new approach and provide a starting point for discussion in the near-term. As AV technology improves and adoption increases in the future, a further reimagining of drive cycles and testing is required. This paper is organized as follows. First, the current drive cycles used for fuel economy testing are discussed. This is followed by a review of current literature and a description of the proposed addition to the current test. Next the ACC behavior used for testing is described and the fuel consumption model discussed. Finally, the results are discussed and their sensitivity to assumptions is tested.

1.1. Current drive cycles

Currently the EPA requires five separate drive cycles for passenger vehicle fuel economy testing. These are the Urban, Highway, High Speed, Air Conditioning, and Cold Temperature tests. While the first three are permitted to be tested in any temperature between 68 °F and 86 °F, the latter two must be done at 95 °F with the air conditioning on and 20 °F, respectively (EPA, n.d. B). The results of these cycles are then weighted in four different ways to find the emissions rate, urban and freeway fuel economies and combined fuel economy. This research uses the urban (FTP) and highway (HWFET) drive cycles, as the basis for the new autonomous drive cycles.

The urban drive cycle (FTP) simulates typical travel through a city with stops and acceleration changes, while the freeway drive cycle (HWFET) simulates smoother freeway travel and makes no complete stops until the end of the test. Figs. 1 and 2 show the velocity schedules for the FTP and HWFET drive cycles respectively, while Table 1 summarizes some of the test details. Also worth noting is that the FTP calls for a cold engine start. This is important as the engine typically operates at its highest efficiency after warming up (EPA, n.d. B).

1.2. Previous research

Rakha et al. developed the Virginia Tech Comprehensive Power-Based Fuel Consumption Model (Rakha et al., 2011). This model was produced in response to two problems found with other available fuel consumption models. The first is that

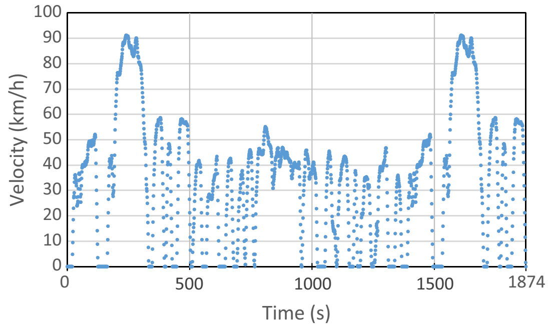

Fig. 1. Velocity schedule of the EPA FTP drive cycle (EPA, n.d. B).

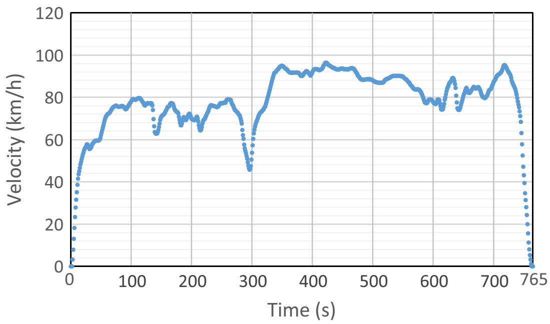

Fig. 2. Velocity schedule of the EPA HWFET drive cycle (EPA, n.d. B).

Table 1
U.S. EPA drive cycles details (EPA, n.d. B).

Driving schedule attributes	FTP	HWFET
Top speed (km/h)	90.1	96.6
Average speed (km/h)	34.1	77.7
Maximum acceleration (km/h/s)	5.3	5.1
Distance covered (km)	17.7	16.6
Time elapsed (min)	31.2	12.75
Individual full stops	23	0
Percentage of time stopped	18	0

many models tend to produce unrealistic optimization decisions, such as always maximizing acceleration until the target speed is reached (Rakha et al., 2011). The second is that many require non-public or inaccessible information on vehicle and engine characteristics. Their model was designed to only require EPA or European Fuel Economy ratings and manufacturer-provided physical vehicle characteristics. Further investigations and field tests were led by Park et al. to determine the accuracy of the model for real world driving (Park et al., 2013). While errors were found, they were found to generally be relatively small and manageable. Edwardes and Rakha then expanded this model to include light duty and hybrid buses and found average errors of 4.7% and 22% for laboratory and on-road fuel consumption testing, respectively (Edwardes and Rakha, 2014).

Gonder and Simpson (2006) investigated the Society of Automotive Engineers (SAE) J1711 testing recommendation standards for plug-in hybrid vehicles. They discussed potential improvements to the standard, some of which have since been adopted in an adapted form by the EPA. These include separately reporting petroleum product consumption and electricity consumption, per unit of distance. Additionally they recommended the assumed charging frequency be increased and a method for determining the weights for the Full, Partial, and No charge test results.

Bhavsar et al. (2014) investigated energy reduction strategies for connected plug-in hybrid vehicles. They tested four strategies: a base case strategy with conventional driver behavior; an optimization strategy using knowledge of the current traffic signal status of approaching intersections; a strategy using information of the headway of all leading vehicles; and a strategy using both information on the headways of all leading vehicles and any approaching light's status. Traffic behavior for these driver scenarios was simulated and used to estimate fuel consumption. They simulated results for both full and partial technology adoption. For full adoption they found fuel consumption savings of 75% for the combined strategy, 71% for the intersection only strategy and 69% for the headway only strategy (Bhavsar et al., 2014).

Wu et al. (2014) investigated the performance gains that could be expected from partial vehicle automation when using information of the current traffic signal status and schedule for the approaching intersection, when compared to human drivers given the same information. In the manual drive case the dashboard would indicate target velocities when approaching an intersection and the driver would attempt to obey the advice. This was tested on a track with real drivers and their speed profiles recorded. A speed profile was then developed to show what would have happened had the advice been followed perfectly in the assumed partial automation case. Fuel consumption was simulated using the EPA's Motor Vehicle Emission Simulator. Partial automation was found to improve fuel consumption by approximately 5–7% compared to a human driver given similar instructions (Wu et al., 2014).

Rajamani and Shladover (2001) investigated cooperative adaptive cruise control (CACC) systems to ascertain the highest capacity gains and decreases in headway possible. They found a decrease of headway to 1 s possible along with a near doubling of capacity from 3000 vehicles/lane/hour for just an ACC system to 6400 vehicles/lane/hour for CACC systems. Kesting et al. (2008) developed an ACC strategy that would adapt its behavior to different traffic patterns. The system is able to autonomously determine if traffic conditions are in 1 of 4 states, and then adjust behavior to the most capacity and flow efficient response. Through simulations they found that equipping just 5% of a vehicle fleet with this technology could significantly decrease congestion and decrease travel times. Grumert et al. (2015) investigated setting variable speed limits for cooperative and autonomous vehicles to moderate traffic patterns and decrease emissions. They found significant increases in traffic harmonization and decreases in vehicular emissions when variable speed limits were used and as the portion of cooperative autonomous vehicles increased.

Feng et al. (2015) investigated using connected vehicles to decrease delays at intersections. Using connected vehicles as sensors to detect non-connected vehicles, they found that delays would decrease as more vehicle-to-infrastructure (V2I) enabled vehicles entered the road. With 100% connected vehicle penetration they found up to 16% reduction in vehicular delays at intersections.

Zlocki and Themann (2014) estimated the fuel reduction potential of different adaptive cruise control strategies. They defined fuel reduction potential as the maximum possible in the most optimal conditions for a particular control strategy when facing a specific situation. Among the 10 different strategies they tested they found potential fuel reductions of up to 85%. On controlled track testing they found reductions of up to 70%, for one specific and short (less than 1 km) scenario. It is notable that they were not including driver comfort, acceptance, or average use conditions. Finally, several recent works have bounded the energy implications from automated vehicles (Anderson et al., 2014; Brown et al., 2014; Fagnant and Kockelman, 2014, 2015; Feng et al., 2015; Folsom, 2012; Gonder et al., 2012; Greenblatt and Saxena, 2015; Iii et al., 2014; Shladover, 2012; Wadud et al., 2013), but fuel economy modeling and implications remains a critical research need.

1.3. Proposed addition to current testing for autonomous vehicles

In order to account for computer agency in automated vehicles, we propose the addition of "Automated Drive Cycles" to the fuel economy testing regimen. These drive cycles would be specific to the individual ruleset that a particular AV will follow, and appropriate for near-term conditions when AVs are on the road with primarily conventionally-driven vehicles. We propose that the AV cycles be generated as simply as possible, with the following method and assumptions:

- First the ruleset that the AV will follow will be abstracted to function in a one dimensional simulation, therefore lateral control can be ignored.
- The road will be assumed to be straight, single lane, and level, with only two vehicles and no traffic control systems.
- The vehicle will be assumed to start 5 m behind another "lead vehicle".
- At time 0 the lead vehicle will start to obey the EPA drive cycle for either FTP or HWFET conditions.
- The simulated AV will then make decisions about how to best follow the lead vehicle until the end of the test.
- The test will end at the completion of the EPA cycle, when the lead vehicle has stopped, regardless of whether or not the AV has stopped.
- The velocity profiles for both the Urban and Freeway simulations will then be recorded.
- The results can be audited and validated as necessary by physical experiments on a roadway.

The next step is to use these drive cycles in dynamometer testing to estimate fuel consumption. These results can then be either weighted in the fuel consumption and emission ratings, or used separately for advertising purposes. This method was designed to conform to the existing standards as much as possible. For more advanced automation features, such as vehicle-to-vehicle and vehicle-to-infrastructure communication, new simulations would need to be developed under future research. Should the EPA add on-road testing to emissions and fuel economy testing, on-road AV following could also be added.

One commonality that all vehicle-to-vehicle and vehicle-to-infrastructure control strategies have is enabling the connected vehicle to predict future constraints on its driving behavior. While specific simulation scenarios would be needed to capture these effects, the possible range of cumulative effects on fuel efficiency can be estimated by giving the following vehicle knowledge about the lead vehicle actions into the future for the above simulation. This would allow insight into the significance of these effects for expected future scenarios of predictive ability.

This approach relies upon manufacturers to simulate and abstract their own rulesets to derive their AV drive cycles. This however, is not significantly different than the status quo, where manufacturers perform their own fuel economy testing and are subject to auditing. Simulated drive cycles can be physically audited by having an AV follow a vehicle, driven to follow the EPA drive cycles on a test track.

2. Methods

2.1. Autonomous drive cycle simulation

The Autonomous Drive Cycle was derived from the EPA City (FTP) and Highway (HWFET) fuel economy testing cycles; and a set of rules describing how an autonomous vehicle would react to a leading car. The EPA drive cycles provided the velocity of the vehicle on a 10 Hz cycle (EPA, n.d. C). The position and acceleration used the integral and derivative of each 1/5 second's position pairs, respectively. This information was then entered into a program that would query the lead vehicle's position and velocity, in meters and m/s every 1/10 s and calculate headway, placing the lead vehicle five meters ahead at time 0. At the end of each time step the simulation would query a set of rules to obtain the velocity and acceleration for the beginning of the next time step. At the end of each time step the autonomous vehicle's position, velocity and acceleration were recorded.

2.2. Autonomous driving behavior

Car following behavior was divided into different sets of rules. These rules included basic ACC and CACC methodologies. The ACC method is meant to simulate basic ACC systems, similar to those already on the market. The CACC method is meant to simulate posited and in-development technology that would allow vehicles to communicate with each other and infrastructure to improve traffic flow. All specific methods used in this paper are basic and generalized to run on all vehicles. They are not necessarily the most optimal for fuel efficiency. The primary contribution of this research is the process for testing the fuel economy of autonomous vehicles and deriving the autonomous drive cycles, rather than optimizing the control methods that lead to those cycles.

Two basic ACC methods were developed and tested. The first, termed HeadwayACC, follows a simple set of bounding rules and direct calculation of the exact acceleration needed to achieve minimum safe following distance or headway and the acceleration needed to achieve the desired headway. Both headway and distance measures are needed to correct for headway approaching ∞ as the velocity approaches 0. The goal of the strategy is to attempt to reach and maintain a target headway behind a lead vehicle. The rules are described in Eqs. (1)–(5) and the variables are defined in Table 2.

Eq. (1) describes the acceleration necessary to reach the minimum safe following distance by the next time step. The first two terms determine the acceleration to close the distance to 0 m and the third term is to ensure a safe distance, either in terms of a minimum distance or headway. Eq. (2) is used to determine whether to use minimum headway or minimum space as the target in Eq. (1). Eq. (3) determines the acceleration necessary to reach the target headway behind the lead vehicle by the next time-step. The equation is derived from the general form equation of motion with constant acceleration, the relative

Table 2
Variable definitions for Eqs. (1)–(10).

Variable name	Definition
a_{safe}	Acceleration to reach minimum safe headway
a_{target}	Acceleration to reach desired headway
v_{self}	Current follower velocity
a_{new}	Decided acceleration
$a_{max,min}$	Min & max acceleration/deceleration
v_{lead}	Current leader velocity
$s = space$	Current space
$headway$	Current headway
$headway_{min}$	Minimum safe headway = 3 s
$T_d = headway_{target}$	Target headway
$buffer$	Minimum safe spatial distance (m)
$step$	Time step duration = 0.1 s
v_d	Desired speed
v_e	Speed error, difference between current and desired velocities
a_{sc}	Acceleration by speed control
s_d	Desired spacing
s_e	Spacing error
$t_{horizon}$	Planning horizon
$t_{interval}$	Planning interval
p_{lead}	Absolute position of the lead vehicle
p_{self}	Absolute position of the following vehicle

velocities of the two vehicles, the current space between the two vehicles and the target headway. Eqs. (4) and (5) are used to compare the two previous determined accelerations to the acceleration bounds and choose an acceleration. The second part of the "and" conditional in Eq. (5) is necessary to correct for when accelerating, a_{safe} will close the gap beyond the target headway. Here a_{safe} is only used for decelerations.

$$a_{safe} \geqslant \frac{space}{step^2} + \frac{v_{lead} - v_{self}}{step} - \frac{buffer}{step^2} \tag{1}$$

$$buffer = \max\left(1\ \mathrm{m}, \frac{v_{self}}{headway_{min}}\right) \tag{2}$$

$$a_{target} = 0.35 * \frac{(space + (v_{lead} - v_{self}) * step) * headway_{target} - v_{self}}{(1 + step^2 * headway_{target})} \tag{3}$$

$$bound(x, y, z) = \max(\min(x, y), z) \tag{4}$$

$$\begin{aligned} &\text{if } a_{safe} \leqslant a_{target} \text{ and } a_{safe} \leqslant 0: \\ &\text{then } a_{new} = bound(a_{safe}, a_{max}, a_{min}) \\ &\text{else}: \ \ a_{new} = bound(a_{target}, a_{max}, a_{min}) \end{aligned} \tag{5}$$

The 0.35 constant in Eq. (3) is to smooth acceleration patterns and was derived through trial and error, as were the minimum safe headway and absolute spacing of 3 s and 1 m, respectively. Additionally, the vehicle will not start moving if currently stopped and the lead vehicle is also stopped and less than 5 m ahead. The vehicle will also adjust its acceleration to never exceed 60 mph or go into reverse. This ruleset was tested with acceleration bounds of ±2, 1.5 and 1 m/s^2.

The second ACC method used, VelocityACC, is a modified form of that used in Shladover et al.'s (2012) CACC platoon simulation. VelocityACC's rules are similar to those used by Shladover et al., but with additions to account for the more dynamic driving conditions of urban streets. The goal of this method is to attempt to reach a target speed and maintain that speed, if feasible. This is opposed to the HeadwayACC method where the goal is to reach a target headway. According to Shladover et al.'s original rules the vehicle can be in either speed control or gap control. If in speed control the new acceleration is described by Eqs. (6) and (7).

Eq. (6) calculates the difference between the vehicle's current speed and the predefined desired speed. Eq. (7) then sets the control acceleration at 40% of the speed error, or the acceleration bounds. The 40% constant comes from Shladover et al.'s (2012) original control scheme and functions to smooth out acceleration changes.

$$v_e = v_{self} - v_d \tag{6}$$

$$a = a_{sc} = bound(-0.4 * v_e, a_{max}, a_{min}) \tag{7}$$

In gap control Eqs. (8)–(10) also apply. Eq. (8) defines the desired spacing gap as the product of the desired headway time and the current speed. Eq. (9) defines the spacing error as the difference between the current gap and the desired spacing gap calculated in Eq. (8). Finally, Eq. (10) sets the acceleration with regard to the possible acceleration bounds and a desired acceleration of the sum of the current gap and a quarter of the spacing error.

$$s_d = T_d * v_{self} \tag{8}$$

$$s_e = s - s_d \tag{9}$$

$$a = bound(s + 0.25 * s_e, a_{sc}, a_{min}) \tag{10}$$

Further inclusions were that the vehicle will not start if the lead vehicle is close and stationary, as in the previous control scheme, and that the vehicle will check to see what is the acceleration needed for minimum safe following distance, as in the previous set, and follow that if the car chooses to decelerate inadequately, up to $-2\ m/s^2$.

For this study the desired speed was set as 60 mph and the desired headway as 3 s. The vehicle will enter speed control when spacing is greater than a "speed space" and gap control when under a "gap space" and, when between, will use the last used control set, defaulting to gap control. These spaces are dependent on speed: above 40 mph, freeway speeds, the spaces are 120 and 100 m respectively: between 25 mph and 40 mph, urban speeds, the spaces are 80 and 65 m; and under 25 mph, local speeds, the spaces are 50 and 42 m. The spacing for highway speeds is that used by Shladover et al. (2012) and the others are based upon a 3.7 s headway at maximum speed cutoff, which is roughly what the freeway speed settings use. As with the previous ruleset these rules were tested with acceleration bounds of ±2, 1.5 and 1 m/s^2.

Another control method tested was based upon connected-autonomous features. Greater improvements in acceleration and velocity stability, and therefore fuel economy, can be gained if vehicles communicate information about their current positions, velocities, and future plans with each other. The amount of information that will be shared is currently unknown and the gains from using this information will be influenced by the percentage of vehicles on the road and roadway infrastructure using the technology. A bounding case is a vehicle having perfect information on what conditions will be in front of it for a defined period of time into the future. This can be used as a proxy to estimate the effects the near future of connected vehicle technology may bring to fuel economy of an individual vehicle. The following control method, PlannedACC, was developed to simulate a control strategy under such conditions.

The rules for this PlannedACC cruise control strategy are as follows:

Starting at time 0, the following vehicle will query the lead vehicle's planned position, for the next $t_{horizon}$ and run Algorithm 1.

Algorithm 1: PlannedACC Overview

$a_{try} = a_{max}$
$if\ \ v_{Self} = 0\ and\ v_{Lead} = 0\ and\ space < 10:$
$\quad then: \ a_{new} = 0, \qquad break\ \#\#\ vehicle\ remains\ stopped$
$for\ t \leqslant t_{horizon}\{$
$\quad if\ \ a_{try} < a_{min}: break\ \#\#\ deceleration\ threshold\ exceeded$
$\quad v_{try} = v_{self} + a_{try} * step$
$\quad p_{try} = p_{self} + v_{try} * step$
$\quad space_{try} = p_{lead}(t) - p_{try}$
$\quad headway = (space_{try})/v_{try}$
$\quad if\ space_{try} < 5\ \mathrm{m}\ or\ headway < headway_{min}:$
$\quad then: a_{try} = a_{try} - 0.1, \quad t = 0$
$\quad else: \ t = t + step\}$
$a_{new} = a_{try}$

This process is then repeated every $t_{interval}$ seconds. Additionally the vehicle will ensure that it does not exceed the speed limit or reverse. The 5-m absolute space minimum was found through trial and error to be the point where gains in safety dropped off considerably. These rules are explained verbally below.

- The following vehicle will query the lead vehicle's position, in relationship to the following vehicle's current position, every 1/10 s for the following X seconds. Various values of X are tested.
- The following vehicle will then determine if it can accelerate at a user defined maximum acceleration for the following X seconds.
  - o If the vehicle falls within a user specified minimum buffer of absolute space or time headway, then the vehicle will then try again at a lower acceleration, continuing until it finds a solution or reaches and uses a user defined minimum (de)acceleration.
    - If the vehicle is ever assumed to exceed the speed limit or reverse, the software will replace the velocity for that time-step with either the speed limit or a stop, respectively.
- The vehicle will then travel for the next Y seconds at the decided upon acceleration, after which it will start the process again.
  - o With Y always being less than X
    - $X - Y$ must be greater the minimum headway
- In addition the vehicle will not start from a stop if the lead vehicle is also stopped and within a user defined buffer space.

This method is designed to stabilize the acceleration curve, minimizing the number of times acceleration changes. This would be expected to reduce fuel consumption. This was tested 4 times, with acceleration bounds of ±1 and 2 m/s^2 and X–Y pairs of 3–2 and 5–3 s. This allows testing of what the possible gains from connected vehicle features may be as their predictive ability increases. This method is not appropriate to measure any specific connected vehicle control function. Rather it models how far into the future a vehicle following a similar control strategy would need to be able to confidently predict the state of the road, in order to deliver fuel efficiency gains. This then acts as an initial proxy for the near- and mid-term feasibility of such a method and technology. Noticeable gains in efficiency at a few seconds of predictive power could be meaningful, but if several minutes of predictive ability are necessary to see changes, one might conclude that it will not be feasible to implement. The parameters for each of the rulesets are summarized in Table 3, with a common maximum speed of 26.8 m/s (60 mph).

2.3. Fuel economy estimation

Fuel Economy was estimated using the Virginia Tech Comprehensive Fuel Consumption Model (Edwardes and Rakha, 2014; Park et al., 2013; Rakha et al., 2011; Saerens et al., 2013). This model relies upon publicly available vehicle and engine characteristics, as well as the official EPA fuel economy ratings for commercially available vehicles. This model has been validated in two separate papers. In a 2011 paper (Rakha et al., 2011) three passenger vehicles, the Ford Explorer, Saturn SL and Honda Accord were put on a dynamometer and run for the Arterial Level of Service (LOS) A cycle, the LA92 cycle and the New York cycle. The instantaneous fuel consumption physically measured was then compared to the model's estimated consumption. They were all highly correlated, with R-squared values exceeding 0.9 and had slopes varying between 1 and 1.3, averaging at 1.1, suggesting slight overestimates in fuel consumption and good predicting power (Rakha et al., 2011).

Park et al.'s 2013 follow-up paper (Park et al., 2013) validates the model against on-road driving, specifically on U.S. Interstate 81 between miles 118 and 132. Notably, unlike a dynamometer, this roadway section includes positive and negative grades. Six light duty vehicles, four passenger vehicles and two SUVs, were tested; a 2001 SAAB 95, a 2006 Mercedes R350, a 2008 Chevrolet Tahoe, a 2007 Chevy Malibu, a 2008 Hybrid Chevy Malibu, and a 2011 Toyota Camry. A DashDAQ unit was used to record speed and fuel consumption and cruise control was both used and not used an equal number of iterations for each vehicle. Using the default model calibration settings, the averaged R-squared values for each vehicle's instantaneous fuel consumption, measured and estimated, were found to be between 0.90 and 0.98, while the slopes were between 0.97 and 1.02, showing consistent goodness of fit, in aggregate (Park et al., 2013). Individual tests were not as good, with R-squared values as low as 0.8 and slopes between 0.72 and 1.62, showing somewhat less goodness of fit (Park et al., 2013). For overall fuel economy this led to a difference of up to ±36% between measured and estimated values (Park et al., 2013). However, what is most important is that the Virginia Tech Comprehensive Fuel Consumption Model correctly states whether a certain driving pattern is more or less efficient than another one. In terms of cruise control versus manual driving and driving northbound or southbound both the measured data and the modeled results showed the same trends in either direction (Park et al., 2013).

The Virginia Tech Comprehensive Fuel Consumption Model, was therefore seen as appropriate for this research. We only used vehicles that at least one of the two validating papers had used. We used the 2010 Honda accord used in (Rakha et al., 2011) and the 2011 Toyota Camry, the 2007 Chevy Malibu and 2008 Chevy Malibu Hybrid, used in (Park et al., 2013). The vehicle parameters we used are identical to the ones used in these validating papers. This gives a comparison of three different manufacturers and a separate test for hybrid vs. conventional vehicles.

The model requires certain vehicle characteristics as inputs and a 1 Hz velocity schedule. As the vehicle following simulation used 10 Hz, every 10th point of velocity was used. While the greater precision was necessary for the control function, it was determined that it would not considerably increase accuracy for fuel economy estimation. The vehicle characteristics used are listed in the Appendix A. The program outputs a file containing the instantaneous consumption of fuel, in liters per second. This was summed to find the total fuel consumption for each control strategy and cycle combination. The total distance that the automated vehicle traveled was then computed and divided over the fuel consumption to find the fuel economy, which was then converted to miles per gallon (mpg).

3. Results

3.1. Drive cycles

The purpose of developing the automated driving rules and cycles was to enable comparison of the plausible differences in fuel efficiencies for autonomous and human driving. One of the methods that an autonomous vehicle can use to improve fuel economy is to lower the magnitudes of its acceleration and deceleration and how quickly it changes acceleration and deceleration. It can be expected in most cases that a drive cycle where these are moderated would be more efficient than another, all else being equal. This study used the FTP and HWFET drive cycles as the basis for a representative human driver and assumes that an automated vehicle would be following a human-driven car. Therefore improvements will come from the vehicle deciding to lower the amplitudes of accelerations and decelerations, which is directly set by the rules, and the smoothness of changes in accelerations and decelerations. Appendix A shows the acceleration schedules for each of the simulated control strategies.

As shown in Figs. A1–A15, the HeadwayACC method performs similarly to the Velocity method. Both have higher acceleration bounds and similar rates of change in acceleration as compared to the EPA's cycles. The PlannedACC ruleset keeps the vehicle's acceleration bounds lower than the EPA's, even when allowed more, and produces much slower changes

Table 3
Ruleset parameters ("N/A" indicates an unused parameter).

Rule set	Normal acceleration bounds (m/s^2)	Maximum deceleration for safety (m/s^2)	Plan ahead time (s)	Planning interval (s)	Target headway (s)	Minimum headway (s)	Minimum safe distance (m)
HeadwayACC 1	±2	−2	N/A	N/A	3	N/A	1
HeadwayACC 2	+1/−1.5	−2	N/A	N/A	3	N/A	1
HeadwayACC 3	±1	−2	N/A	N/A	3	N/A	1
VelocityACC 1	±2	−2	N/A	N/A	3	N/A	1
VelocityACC 2	±1.5	−2	N/A	N/A	3	N/A	1
VelocityACC 3	±1	−2	N/A	N/A	3	N/A	1
PlannedACC 1	±2	N/A	3	2	N/A	1	5
PlannedACC 2	±2	N/A	5	3	N/A	1	5

in acceleration. Therefore it is expected that the HeadwayACC method would have a lower fuel economy, the VelocityACC method a similar or slightly lower fuel economy and the PlannedACC ruleset a higher fuel economy than the car following the EPA's drive cycles.

3.2. Fuel economy

Table 4 shows the fuel economies of a selected set of the drive cycles for the simulated 2010 Honda Accord and the percentage change from the modeled fuel economy for the EPA's drive cycles. The Honda Accord is used as an illustrative example here, but the method is applicable across all vehicle makes and models. The results for all vehicles are shown in Appendix B. The trends seen for the Honda Accord are similar to those of all the other vehicles. The HeadwayACC control method was generally worse than the EPA's cycles, with fuel economy degradations up to 3%. The best performing freeway cycle had a small decrease in fuel economy for all vehicles and the only urban cycle had a fuel economy increase of up to 2%, when the acceleration bounds were largest. Similarly the VelocityACC control strategy had mixed results. For the freeway cycle it mostly showed decreases of up to 3% in fuel economy. Some of the urban cycles showed slight gains and the 2007 Malibu was an outlier, with one of its city cycles showing an increase of fuel economy of 10%. The PlannedACC method always showed improvement in fuel economy, with the greatest gains found in the city cycles, between 2% and 6% gains in fuel economy, and lessor gains, between 1% and 3%, seen in the freeway cycles. This shows that gains in fuel economy can be achieved from just 3 s of predictive ability. These results are consistent with expectations, given the acceleration schedules of the simulated and EPA drive cycles.

All percentage changes were calculated from simulated fuel economies for both the EPA and Automated cycles, to ensure trends in simulated uncertainty are constant. Calibration research on the Virginia Tech Comprehensive fuel consumption model showed that directions and relative magnitudes in fuel consumption changes were accurate, even if absolute values were not perfect (Park et al., 2013; Rakha et al., 2011), ensuring the relative integrity of the results. The occasional losses in fuel economy in HeadwayACC and VelocityACC appear to be due to temporary stability losses caused by an inability of these methods to predict the future and plan ahead.

If the 2010 Accord were equipped with the necessary technology for the above automated control strategies, we can then use the results above to envision what the proposed process would look like. First the process can be simplified to only include the derived autonomous tests and original Urban and Freeway cycles, each weighted evenly with their counterpart, for the urban and freeway rating, respectively. The combined fuel economy rating would follow the current 55% urban 45% freeway split (EPA, 2014). Honda would abstract their vehicle control rules to run on a level straight road and work with complete knowledge of the location of the vehicle in front of it. Honda would then record the velocity schedules and run dynamometer testing, using 4 test cycles, the original 2 FTP and HWFET cycles and their 2 derived ones. The results of both freeway and both urban tests would then be averaged to find the new fuel economy sticker ratings, so for the HeadwayACC control method urban fuel economy would decrease 0.25 mpg, freeway 0.1 mpg and combined 0.18 mg, while with PlannedACC they would rise 1.25 mpg, 0.3 mpg, and 0.82 mpg, respectively. Possible blended fuel economies for other weighting methods are shown in Table 5. This shows a definite benefit for connected autonomous features, as a 1-mpg gain may well improve sales, help with compliance, and reduce emissions. The fully autonomous features could still help or hurt CAFE requirements for different manufacturers. This is especially important as automation is becoming much more common. A 1–3% gain or loss across a full fleet would be considerable. Additionally any fleet gains and losses in fuel economy directly limit or enable increased sales of larger, less fuel efficient, and more profitable vehicles.

3.3. Parameter sensitivity

Both the HeadwayACC and VelocityACC based control methodologies are insensitive to the headway, in most circumstances. In both cases, when the acceleration bounds are held constant, and the headway varied from 2 to 6 s there was no variation in fuel economy. This is because any safe ruleset will normally attempt to keep the desired headway, making any differences temporary until the desired headway is reached. This suggests the acceleration bounds as the main factor in fuel economy, with bounds slightly higher than that of the leading car resulting in the lowest fuel consumption.

Table 4
Fuel economy results: 2010 Honda Accord.

2010 Honda Accord	Simulated fuel economy (MPG)	% Change from EPA
FTP Urban Cycle (22)[a]	25.1	N/A
HWFET Freeway Cycle (31)[a]	43.3	N/A
HeadwayACC City 1	25.6	2%
HeadwayACC Freeway 1	43.1	0%
VelocityACC City 2	25.3	1%
VelocityACC Freeway 2	43	−1%
PlannedACC City 2	26.6	6%
PlannedACC Freeway 2	43.9	1%

[a] Rated fuel economies are notably lower than simulated, due to usage of the extra 3 cycles for the rated fuel economies.

Table 5
Blended fuel economies for 2010 Honda Accord.

ACC ruleset	Traditional cycle weight (%)	Autonomous cycle weight (%)	Simulated weighted fuel economy (MPG)	Weighted% change from EPA
FTP Urban Cycle (22)[a]	100	0	25.1	N/A
HWFET Freeway Cycle (31)[a]	100	0	43.3	N/A
EPA Combined (25)[a]	100 (55% City/45% Highway)	0	33.29	N/A
HeadwayACC City 1	80	20	25.20	0.40
HeadwayACC Freeway 1	80	20	43.26	−0.09
Headway ACC Combined 1	80	20	33.33	0.11
HeadwayACC City 1	60	40	25.30	0.80
HeadwayACC Freeway 1	60	40	43.22	−0.18
Headway ACC Combined 1	60	40	33.36	0.22
HeadwayACC City 1	40	60	25.40	1.20
HeadwayACC Freeway 1	40	60	43.18	−0.28
Headway ACC Combined 1	40	60	33.40	0.33
HeadwayACC City 1	20	80	25.50	1.59
HeadwayACC Freeway 1	20	80	43.14	−0.37
Headway ACC Combined 1	20	80	33.44	0.44
VelocityACC City 1	80	20	25.22	0.48
VelocityACC Freeway 1	80	20	43.24	−0.14
VelocityACC Combined 1	80	20	33.33	0.12
VelocityACC City 1	60	40	25.34	0.96
VelocityACC Freeway 1	60	40	43.18	−0.28
VelocityACC Combined 1	60	40	33.37	0.23
VelocityACC City 1	40	60	25.46	1.43
VelocityACC Freeway 1	40	60	43.12	−0.42
VelocityACC Combined 1	40	60	33.41	0.35
VelocityACC City 1	20	80	25.58	1.91
VelocityACC Freeway 1	20	80	43.06	−0.55
VelocityACC Combined 1	20	80	33.45	0.47
PlannedACC City 3	80	20	25.40	1.20
PlannedACC Freeway 3	80	20	43.42	0.28
PlannedACC Combined 1	80	20	33.51	0.66
PlannedACC City 3	60	40	25.70	2.39
PlannedACC Freeway 3	60	40	43.54	0.55
PlannedACC Combined 1	60	40	33.73	1.32
PlannedACC City 3	40	60	26.00	3.59
PlannedACC Freeway 3	40	60	43.66	0.83
PlannedACC Combined 1	40	60	33.95	1.97
PlannedACC City 3	20	80	26.30	4.78
PlannedACC Freeway 3	20	80	43.78	1.11
PlannedACC Combined 1	20	80	34.17	2.63

[a] Rated fuel economies are notably lower than simulated, due to usage of the extra 3 cycles for the rated fuel economies.

For the PlannedACC control strategy desired headway was not a parameter. Instead, the plan ahead and re-planning intervals were modified to vary between 1 and 6 s for each. As expected, the longer the vehicle plans into the future, the greater the fuel economy benefits. The interval between changes in acceleration however, must be smaller than the time the vehicle plans for. Equal plan ahead and re-plan intervals almost always lead to decreased fuel efficiency and are always less efficient than if they were different, for a given planning interval. The buffer between these two intervals ensures the smoother acceleration pattern, which allows for the efficiency gains. Overall fuel economy gains were shown at all times where the time between restarting the planning algorithm was shorter than the time it could look ahead, suggesting fuel economy gains are possible with any level of predicative ability from connected features.

Decreasing the difference between the planning times, in addition to being less efficient, is also not always safe. For both 2 s and 6 s of planning time vehicles crash when the re-planning time is equal. This is due to the limited headway emphasis and simplifications that ignored rules that would be necessary for safety outside normal operation. Crashes can occur in this method when the speed at which the vehicle is traveling at the end of each re-planning interval is high enough to cover the distance between the vehicles in the time between the re-plan and planning intervals. As the minimum headway is 1 s, any difference less than that can lead to a crash. For example, if over the next 6 s it is found safe to accelerate to 60 mph and the vehicle accelerates for the full 6 s while the lead vehicle is stopped, there will be at least 27 m between the two vehicles before the next decision is made. The maximum 2 m/s^2 will not allow the following vehicle to safely stop within this distance. In reality, all control methodologies would have contingency rules that would allow uncomfortably fast decelerations. This was ignored here, both for simplicity and because the test cycles are not meant to examine extreme situations. Additionally one of the main predicted advantages of connected-autonomous vehicles is the ability to safely reduce headway. Therefore modifying the control rules to increase headway, rather than maintain a difference between the two planning intervals would not represent ultimate likely conditions.

4. Summary and conclusions

Autonomous vehicle driving behavior can have a considerable effect on fuel economy. Here we proposed a standardized method for testing the fuel economy effects of autonomous vehicle behavior when following another vehicle. The method consists of two steps, and is applicable in the near-term, when AVs will travel in traffic with primarily conventional vehicles. First the driverless vehicle's control strategy is abstracted for simulation to a simple one lane and one-dimensional road, with only one leading vehicle and perfect visibility; it is then run following a vehicle obeying the EPA's FTP and HWFET drive cycles. These derived drive cycles are then to be tested with a dynamometer, similar to current testing. A series of simplified rulesets was then developed for ACC behavior and their car following behavior was simulated for the EPA's drive cycles. Fuel economy was estimated using the Virginia Tech Comprehensive Fuel Consumption model. Results showed considerable variation in fuel economy, with the simplest ruleset showing decreases in performance, and a slightly more complicated and less-aggressive ruleset showing both minor improvements and decreases in fuel economy. Another control algorithm, relying upon an assumption of predictive ability provided by connected autonomous vehicles was shown to consistently provide improvements in fuel economy.

The results of this study have shown that following control algorithms designed without considering fuel economy performance can perform significantly worse, while more intelligently designed control schemes may equal or exceed the base driver performance assumed by the EPA fuel economy tests. At present, with no incentive to design more fuel efficient autonomous rulesets, manufacturers may not design for increased fuel economy. They may design a system to maximize speed and/or acceleration, by default or as an option. This would be similar to the poor performing HeadwayACC ruleset we tested, which generally had worse fuel economy than the EPA fuel cycle. In addition, this study found more advanced connected features can improve performance consistently and significantly, by improving the amount of time a vehicle can predict actions in the future. While the basic testing method outlined here would have to be expanded to meet U.S. regulatory requirements in order to test automated vehicles, it does show the need for a new testing procedure. Additionally, while this study did not attempt to find an optimal control function, it is seen that attempting to significantly improve fuel economy without any predictive or connected features is challenging and inconsistent. This is because the lead vehicle's behavior in the EPA tests is fairly non-aggressive, and the rules tested did not account for the full range of behaviors exhibited by the EPA drive cycles. In particular, none of the rulesets explicitly distinguished between abrupt emergency stops and general city stop-and-go traffic. The inability to account for this caused poor performance on the urban cycles, where such actions are common, and may have caused poorer performance than could be expected of vehicles following more robust control sets designed for stop-and-go traffic. Additionally the fuel consumption model used precluded any testing of grade-based optimization or broader fuel economy benefits of automation such as platooning or reduced congestion. This study demonstrated that simulations of a car with autonomous features following another vehicle obeying the EPA drive cycle can be used as a standardized method to create a drive cycle to test fuel economy.

The results suggest that this method can be used to demonstrate how AV behavior may affect fuel economy in vehicles following similar traffic patterns to those currently assumed by the EPA. These results are limited by: the simplification of control strategies; the accuracy of the fuel consumption model used; and the usage of the EPA Urban and Freeway drive cycles, which likely do not reflect the real conditions in which the initial AVs may be operating. With these factors noted, we found a range of possible automation outcomes from fuel economy losses of up to 3% to gains of up to 10%.

This study used the current EPA Urban and Freeway fuel economy drive cycles as the base for the automated following cycles. This may not be appropriate for the expected future of NHSTA Levels 2 and 3 AVs (NHTSA, 2013). These vehicles are not expected to be able to drive themselves in all conditions. Instead they are to have a limited subset of conditions in which they may enter an autonomous mode. Therefore, the leader drive cycle should be designed to account for these situations. In addition, the approach used here is for the near-term evaluation of AV technologies. As technology and adoption increases and the system becomes more efficient, the driving behavior of the lead vehicle as well as the entire system will change. Hence, car following algorithms will have less predictive power. What is clear is that rapid progress is being made in the development of autonomous and connected vehicles and that AV technology affects individual vehicle fuel economy. Given this, stakeholders can use the methods outlined here as a starting point in the discussions for the best path forward.

Acknowledgments

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Appendix A. Control strategy drive cycles and discussion

Figures A1–A15 show the simulated acceleration schedules for each ruleset.

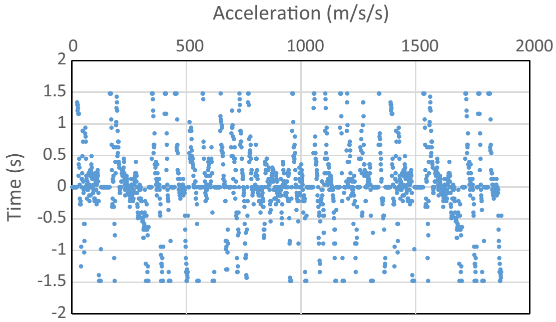

Fig. A1. Acceleration schedule for EPA's urban (FTP) drive cycle.

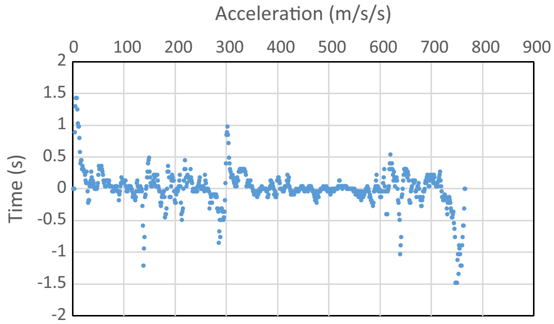

Fig. A2. Acceleration schedule for EPA's freeway (HWFET) drive cycle.

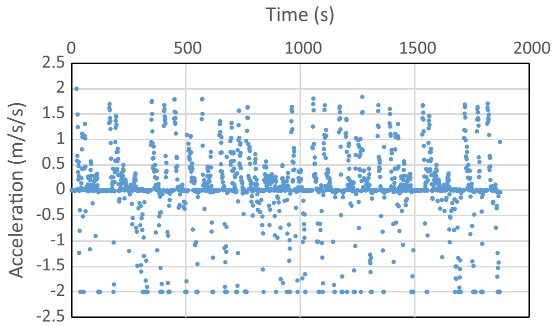

Fig. A3. Acceleration schedule for HeadwayACC 1 urban.

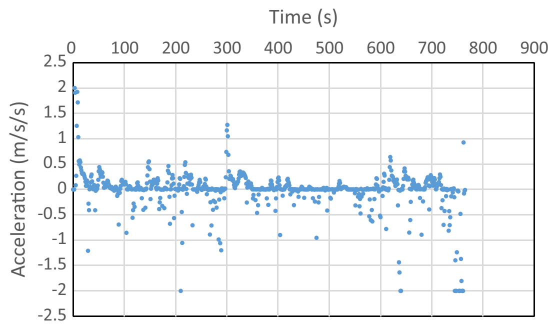

Fig. A4. Acceleration schedule for HeadwayACC 1 freeway.

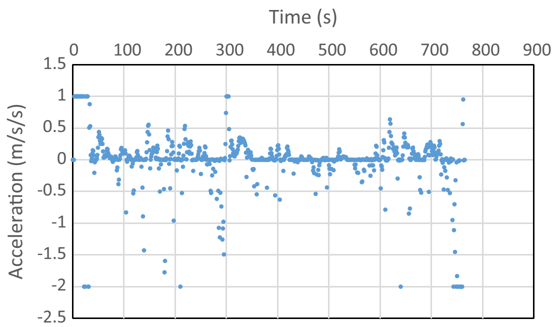

Fig. A5. Acceleration schedule for HeadwayACC 2 freeway.

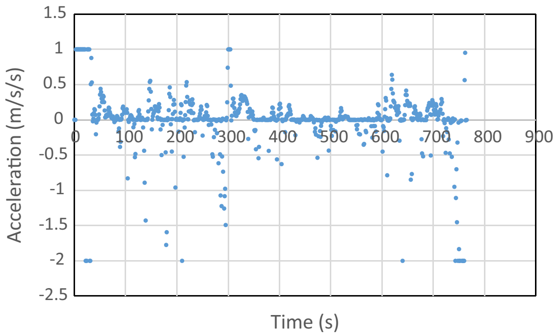

Fig. A6. Acceleration schedule for HeadwayACC 3 freeway.

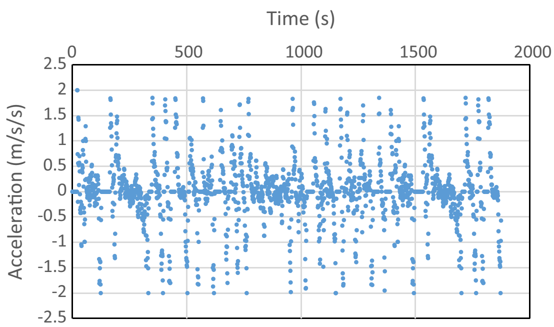

Fig. A7. Acceleration schedule for VelocityACC 1.

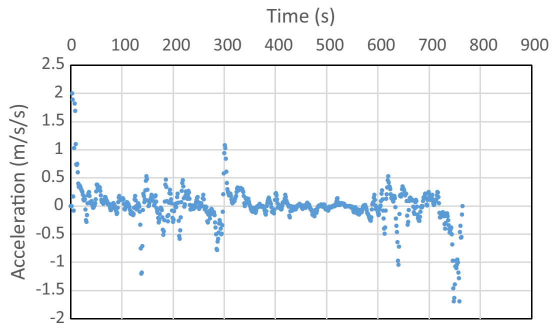

Fig. A8. Acceleration schedule for VelocityACC 1 freeway.

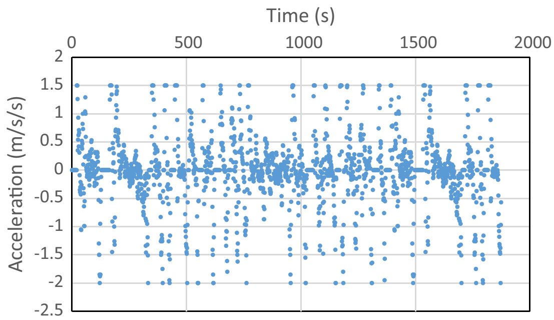

Fig. A9. Acceleration schedule for VelocityACC 2 urban.

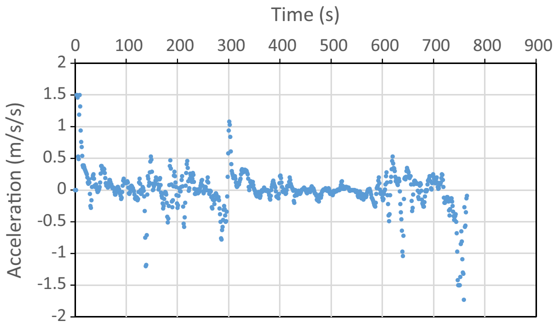

Fig. A10. Acceleration schedule for VelocityACC freeway.

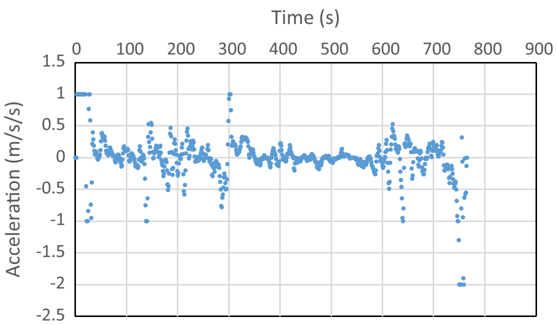

Fig. A11. Acceleration schedule for VelocityACC 3 freeway.

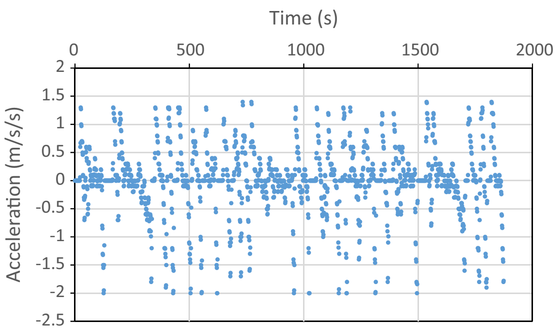

Fig. A12. Acceleration schedule for VelocityACC 3 urban.

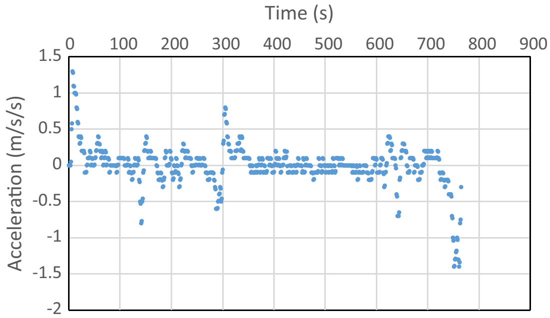

Fig. A13. Acceleration schedule for PlannedACC 1 freeway.

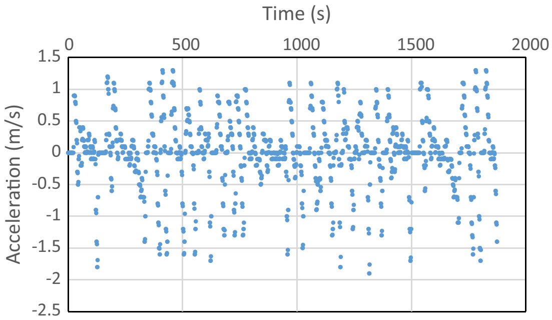

Fig. A14. Acceleration schedule for PlannedACC 2 urban.

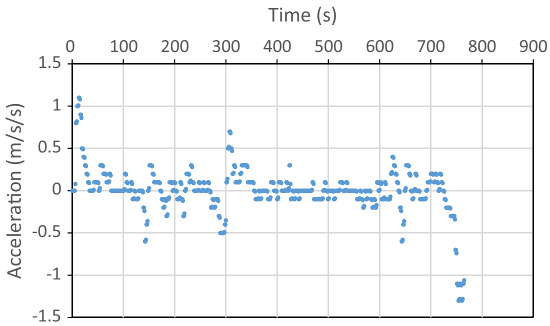

Fig. A15. Acceleration schedule for PlannedACC 2 freeway.

<u>A note on vehicles not stopping at the conclusion drive cycles</u>

As can be seen not all derived drive cycles reached a steady state stop at the conclusion of their cycles, instead only still slowing down. This is because the time of the test was held constant and the control functions are trying to follow a lead vehicle that comes to a complete stop at the end of the test. If the simulated vehicle still has space it will slowly try to close the gap to its predetermined safe distance. These speeds are generally under 1 m/s, but go up to about 6 m/s at conclusion of some tests. This may not be ideal for a physical test. This could be alleviated by giving the simulation vehicles an extra few seconds to reach a complete stop.

<u>A note on HeadwayACC and VelocityACC and Crashing</u>

Both the HeadwayACC and Velocity methods require assumptions about flow stability. The ACC method may cause instability in unstable traffic flow simulations. This can occur when the allowable deceleration bound is less than that of the lead car and when the lead car quickly decelerates. Neither the Headway nor Velocity method always guarantee enough time to slow down at the lower deceleration and will therefore crash. In reality there would be a safety feature to detect rapid slowdowns and respond with special rules, but those were not included here. This was only a problem for the urban cycle when the maximum deceleration was less than 1.5 m/s^2. In these situations a crash would occur. This situation was therefore removed from the results.

Appendix B. Full fuel economy simulation results

Tables B1–B4 show the simulated fuel economy results for each vehicle tested.

Table B1
Simulated fuel economy results for 2010 Honda Accord.

2010 Honda Accord	Fuel economy (mpg)	Percent change from EPA
EPA Urban (FTP)	25.1	
EPA Freeway (HWFET)	43.3	
HeadwayACC Urban 1	25.6	2
HeadwayACC Freeway 1	43.1	0
HeadwayACC Freeway 2	42.2	−3
HeadwayACC Freeway 3	42.2	−3
VelocityACC Urban 1	25.7	2
VelocityACC Freeway 1	43	−1
VelocityACC Urban 2	25.3	1
VelocityACC Freeway 2	43	−1
VelocityACC Freeway 3	42.4	−2
PlannedACC Urban 1	26.4	5
PlannedACC Freeway 1	43.6	1
PlannedACC Urban 2	26.6	6
PlannedACC Freeway 2	43.9	1

Table B2
Simulated fuel economy results for 2011 Toyota Camry.

2011 Toyota Camry	Fuel economy (mpg)	Percent change from EPA
EPA Urban (FTP)	30.6	
EPA Freeway (HWFET)	46.1	
HeadwayACC Urban 1	30.2	−1
HeadwayACC Freeway 1	45.9	0
HeadwayACC Freeway 2	44.7	−3
HeadwayACC Freeway 3	44.7	−3
VelocityACC Urban 1	30.3	−1
VelocityACC Freeway 1	45.8	−1
VelocityACC Urban 2	29.6	−3
VelocityACC Freeway 2	45.8	−1
VelocityACC Freeway 3	44.9	−3
PlannedACC Urban 1	31.4	3
PlannedACC Freeway 1	46.6	1
PlannedACC Urban 2	31.8	4
PlannedACC Freeway 2	46.9	2

Table B3
Simulated fuel economy results 2007 Chevy Malibu Conventional.

2007 Chevy Malibu	Fuel economy (mpg)	Percent change from EPA
EPA Urban (FTP)	23.1	
EPA Freeway (HWFET)	33.7	
HeadwayACC Urban 1	22.9	−1
HeadwayACC Freeway 1	33.6	0
HeadwayACC Freeway 2	32.8	−3
HeadwayACC Freeway 3	32.8	−3
VelocityACC Urban 1	22.9	−1
VelocityACC Freeway 1	33.5	−1
VelocityACC Urban 2	25.5	10
VelocityACC Freeway 2	33.5	−1
VelocityACC Freeway 3	33	−2
PlannedACC Urban 1	23.7	3
PlannedACC Freeway 1	34	1
PlannedACC Urban 2	23.9	3
PlannedACC Freeway 2	34.2	1

Table B4
Simulated fuel economy results 2008 Chevy Malibu Hybrid.

2008 Chevy Malibu	Fuel economy (mpg)	Percent change from EPA
EPA Urban (FTP)	26.9	
EPA Freeway (HWFET)	44.7	
HeadwayACC Urban 1	26.7	−1
HeadwayACC Freeway 1	44.5	0
HeadwayACC Freeway 2	43.5	−3
HeadwayACC Freeway 3	43.5	−3
VelocityACC Urban 1	26.7	−1
VelocityACC Freeway 1	44.4	−1
VelocityACC Urban 2	26.3	−2
VelocityACC Freeway 2	44.4	−1
VelocityACC Freeway 3	43.7	−2
PlannedACC Urban 1	27.5	2
PlannedACC Freeway 1	45.1	1
PlannedACC Urban 2	27.7	3
PlannedACC Freeway 2	45.4	2

Appendix C. Vehicle characteristics for Virginia Tech Comprehensive Fuel Consumption Model (VTCFCM) (Edwardes and Rakha, 2014; Park et al., 2013; Rakha et al., 2011; Saerens et al., 2013)

Description	Accord	Camry	Malibu	Malibu Hybrid
Model Year	2010	2011	2007	2008
Wheel Radius (m)	0.3322	0.3322	0.32375	0.3322
Redline RPM	6800	6300	6000	6000
Drag Coefficient	0.30	0.28	0.34	0.34
Frontal Area (m^2)	2.32	2.424	2.318	2.313
Wheel Slippage	0.035	0.035	0.035	0.035
Cylinders	4	4	4	4
Engine Liters	2.354	2.5	2.2	2.4
Gears	5	6	4	4
1st Gear Ratio	2.652	3.54	2.96	2.96
2nd Gear Ratio	1.517	2.05	1.62	1.62
3rd Gear Ratio	1.037	1.38	1	1
4th Gear Ratio	0.738	0.98	6.8	6.8
5th Gear Ratio	0.566	0.74	0	0
6th Gear Ratio	0	0.66	0	0
Final Drive Ratio	4.44	3.82	3.63	3.63
Mass (kg)	1453	1500	1440	1604
Urban Rating (mpg)	22	22	24	24
Freeway Rating (mpg)	31	33	34	32
Rolling Coefficient	1.75	1.75	1.75	1.75
C1	0.0328	0.0328	0.0328	0.0328
C2	4.575	4.575	4.575	4.575
Driveline Efficiency	0.92	0.92	0.92	0.92
Idling Speed (rpm)	700	660	680	660

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