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Fuel consumption of adaptive cruise control platoons: bench experiments and data-driven estimation for real traffic

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Abstract

Vehicles equipped with adaptive cruise control (ACC) systems are expected to improve traffic safety and decrease fuel consumption. Recent experimental studies have shown that ACC leads to string instability in the case of platooning and can, therefore, result in higher energy needs compared to a platoon of human-driven vehicles (HDV). However, the impact of the ACC on fuel consumption in the case of platooning and the global impact of ACC overconsumption in traffic is not known yet. This study examines the impact of ACC systems on traffic consumption using experimental data and traffic records. In this study, we inject the speed profiles of ACC and HDV platoons that follow a similar leader trajectory into an engine bench. Then, we identify the event that leads to an overconsumption in the case of platooning. The results of the engine bench show that only ACC platoons of six or more vehicles with a short time-gap setting consume more than HDV platoons. Using HighD and ExiD records, we detect if the events leading to overconsumption often happen in traffic. The results on HighD and ExiD show that such an event happens once out of 1250 if we divide the time into steps of 15 seconds. This shows that, even if overconsumption exists in specific cases, those cases are actually too rare in traffic to impact global fuel consumption.

Keywords: adaptive cruise control, fuel consumption, engine bench, traffic dataset.

Introduction

Adaptive cruise control (ACC) is defined as level one out of five levels of vehicle automation by SAE International (1). These systems are increasingly prevalent on US and EU roads, and their market penetration rates should approach 25 % in 2030 (2). Manufacturers claim that their systems, although designed to increase driver safety and comfort, will reduce vehicle consumption (3). Penetration rates could grow faster as a company has developed software that equips any compatible vehicle with an SAE level 2 system (4). The software is open source on GitHub (5) and is expected to become widely used (6, 7).

Some recent studies have collected ACC platooning trajectories during experiments (8, 9). Further studies based on these data have analysed the impact of ACC on road capacity by creating fundamental diagrams (10, 11) and have found that ACC can decrease road capacity up to 25 % for a 100 % ACC penetration rate (11). Other studies (9, 12–14) have shown that ACC vehicles in a platoon tend to create string instability (15). The system generates a deceleration overreaction followed by an acceleration overreaction that propagates to the other vehicles in the platoon, increasing in magnitude. This deceleration-acceleration overreaction is not observed in human-driven vehicles (HDV) platoons following the same trajectory (14). It might reduce traffic

safety levels and increase fuel consumption, contrary to the manufacturers' claim.

The specific topic of ACC fuel consumption has been studied since the beginning of ACC commercialization. Some early studies determined that ACC, depending on its algorithm and the chosen setting, would consume between 8 and 28 % less fuel (16). However, this result was based on assumptions, not experimental data with ACC vehicles. Other studies have focused on developing eco-driving algorithms for ACC systems to reduce fuel consumption (17). Some models (14, 18) were developed based on data collected in ACC platoon experiments (8) and have found a link between the string instability produced by ACC platoons and an increase of the energy that the car needs to progress compared with HDV platoons (19).

String instability can appear only when vehicles are in a platooning formation. In any other situation, the time gap is large enough for at least one ACC vehicle to switch back to cruise control mode. This would cut the wave of overreaction and limit the magnitude of string instability. If

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the ACC vehicles are not in a platooning formation, they will drive at a constant speed. The constant speed is the condition when the car consumes the least (20). In other terms, if an ACC is not in car-following mode, it does not consume more than an HDV vehicle using cruise control. Furthermore, in the case of only two vehicles in a platoon, a previous study (8) shows that the overreaction from the follower is very limited, and it is improbable that this would significantly impact fuel consumption. Consequently, at least three vehicles are needed to observe string instability that would lead to fuel overconsumption compared to the same formation of HDV vehicles. In the case of a mixed platoon ACC and HDV, the human drivers will likely cut the string instability wave in the case of a mixed platoon HDV and ACC. This would compensate for the impact of ACC vehicles within the platoon. Based on this hypothesis, we assume for this study that ACC vehicles hurt fuel consumption if and only if they are in a platooning formation composed of ACC.

In summary, the previous studies have shown that the ACC vehicles tend to overreact. In the case of platooning, this overreaction propagates all over the platoon and leads to an increase in the need for energy consumption. However, those results cannot be transposed directly to estimate the fuel consumption of ACC platoons, as it is not necessarily a linear function of energy needs. This study aims to estimate the potential overconsumption more accurately using an experimental setup and trajectory data. We propose the framework presented in figure 1 to address this question.

The first step comprises two substeps: in step 1.1, we select trajectories of ACC and HDV in a platooning experiment on a test track to pick up the platoons with the most similar leader profiles. To do so, we use OpenACC data (8). Second, we inject the trajectories in an engine test bench to determine the impact of automation on consumption in the case of platooning. Those two steps, 1.1 and 1.2, are described in the next part. Third, we identify the specific events that might trigger a difference in consumption within a trajectory. Finally, we examine how often these events might happen in real-life traffic based on traffic datasets. This part uses HighD and ExiD datasets (21, 22). Steps 2.1 and 2.2 are described in the third section. A discussion and conclusion part ends the paper.

Fuel consumption in an engine bench experiment

Data selection

Speed and acceleration profile, road gradient, vehicle characteristics, and local weather influence fuel consumption. To make a fair comparison, we must analyze vehicles following a platoon leader with a similar speed profile in the same environment. This requirement is met by a dataset collected in the experiment on the Zalazone test track during the OpenACC campaign by the JRC team (8, 12).

The goal was to analyze the impact of long platoons of ACC vehicles (i.e., 10 to 12 vehicles), with the same leader trajectories. The vehicles were driven either manually or with the ACC activated. When the ACC system was activated, several time gap settings were tested. Each vehicle was a different make and model, and the vehicle order was changed between experiments with short, long, and medium time gaps.

However, even if the vehicles were all of different makes and models, they were all sedans with roughly the same shape. The engine from one vehicle to another produces a similar level of power.

This implies that the engine type influence on consumption in this experiment is, at most, negligible. Their minimal headway is, except for a fraction of a second, always larger than twice the length of an individual car, which means that vehicles do not benefit from the slipstreaming phenomenon (23).

The shorter the time gap, the more reactive the response of the following vehicle. Two different experimental conditions were tested. In one experiment (condition A), the leader vehicle imposed significant decelerations and accelerations. In the second one (condition B), the leader drove as much as possible at a constant speed, and the speed variations were only due to the road geometry. An extensive data description was presented in (12). The comparison of the two experimental conditions has shown that condition A leads to emergency braking, which rarely happens in real traffic on freeways. Thus, we decided to focus on the trajectories in experimental condition B as their deceleration-acceleration phases are more likely to be observed in real traffic. The goal is to select the HDV and ACC trajectories with the most similar leader speed profile.

We first separated the platoons into groups based on their mean speed ($8m/s$, $11m/s$, $14.5m/s$, and $17.5m/s$) and their setting (HDV, ACC with short time gap setting, ACC with long time gap setting or ACC platoons with different settings from one vehicle to another). The data were collected at 10 Hz through sensors placed inside the vehicles. For each group (same mean speed and setting), we compared all the first recorded trajectories and selected the platoon with the most similar first-recorded trajectories. This first recorded trajectory corresponds to the first follower, as the leader's trajectory is not included in OpenACC.

To do so, we compute for each first-recorded trajectory the distance with every other first-recorded trajectory that does not belong to the same platoon group* using the dynamic time warping algorithm (24). This allowed us to identify a platoon for each ACC setting with the closest first-recorded trajectory, leading to the selection of four platoons. Figure 2 presents the speed profiles. In all ACC trajectories, we notice

*e.g., if the trajectory belongs to a short time gap platoon, we compare it with either long time gap, mixed time gap or HDV platoons

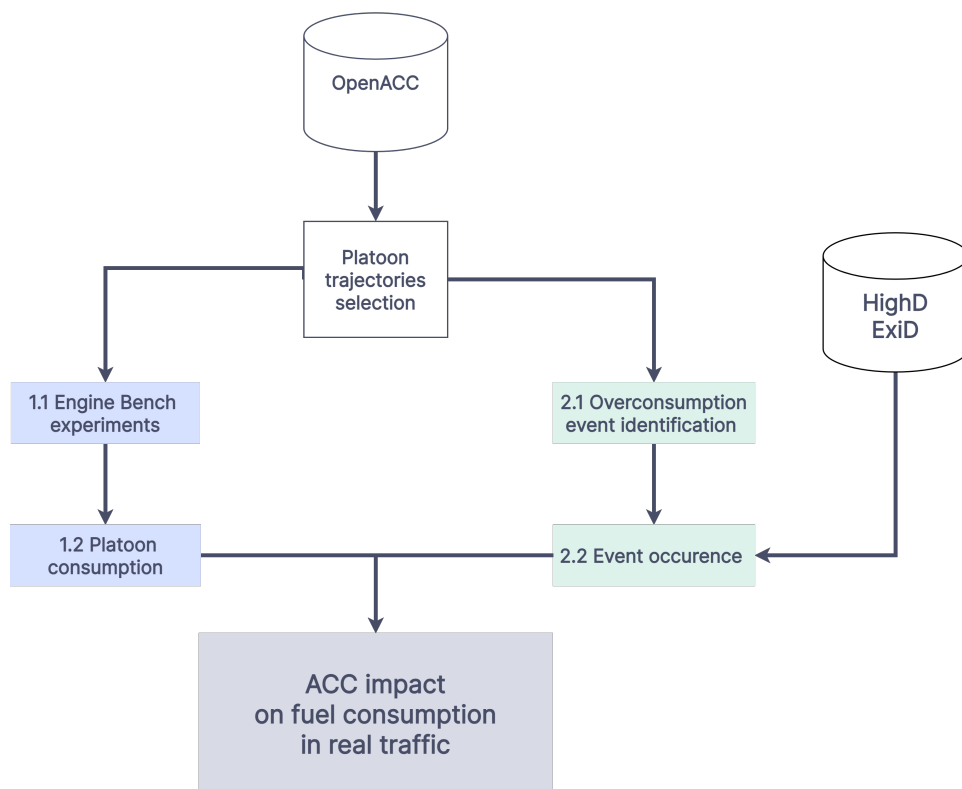


Figure 1. Flowchart of the study. Blue boxes indicate the substeps used to determine the consumption of ACC platoons. Green boxes represent the substeps to determine the frequency of the trajectories used in the bench experiment in motorway traffic.

two large deceleration-acceleration patterns. According to Li and al. (13) and Ciuffo and al. (14), string instability always follows these events. String instability can be observed in all platoons included in the dataset, no matter the order of the vehicle models. In the case of short-time gap platoons, the string instability is more important (see 2) and leads to harsher decelerations and accelerations compared to the other trajectories. This shows that short time gap ACC platoons tend to accelerate more than other ACC platoons or HDV platoons.

Given that the obtained data were partially incomplete (less than one percent of the points were missing), we interpolated the missing points using a linear interpolation scheme. Then, we applied the kernel regression to the data to smoothen it before testing it on the engine bench. In the test bench, we used only the follower’s trajectories because the leader’s trajectory was recorded at a 1Hz rate instead of a 10Hz rate due to technical limitations, and this sampling rate is too low for the engine bench.

Engine bench experiment

The principle of the real-time experiment consists of controlling a real engine in the bench while simulating the driveline and the resistive force of the vehicle. The engine is

petrol from a Renault Kadjar TCE130, and its characteristics are presented in table 1.

Table 1. Hardware in a loop engine characteristics that were used during the experimentation.

Component	Characteristics	Value
Vehicle engine	weight	1350 kg
	displacement	1197 cc
	max power	96 kW @ 5500 rpm

The engine follows the indicated instructions computed by the VEHLIB model, a Simulink package created by the Université Gustave Eiffel (25). In detail, the models work in power hardware in the loop mode: a simulated vehicle controller follows the desired speed by choosing the correct gear number at each time step and sending a throttle value to the engine controller. An energetic vehicle model runs in the real-time processor and interacts with the bench. The VEHLIB library is also used to interface data and the engine. Sensors placed all over the engine allow one to record indicators such as engine torque, temperature, fuel consumption, and fuel density. Engine torque is then re-injected in real time into the VEHLIB model, which estimates

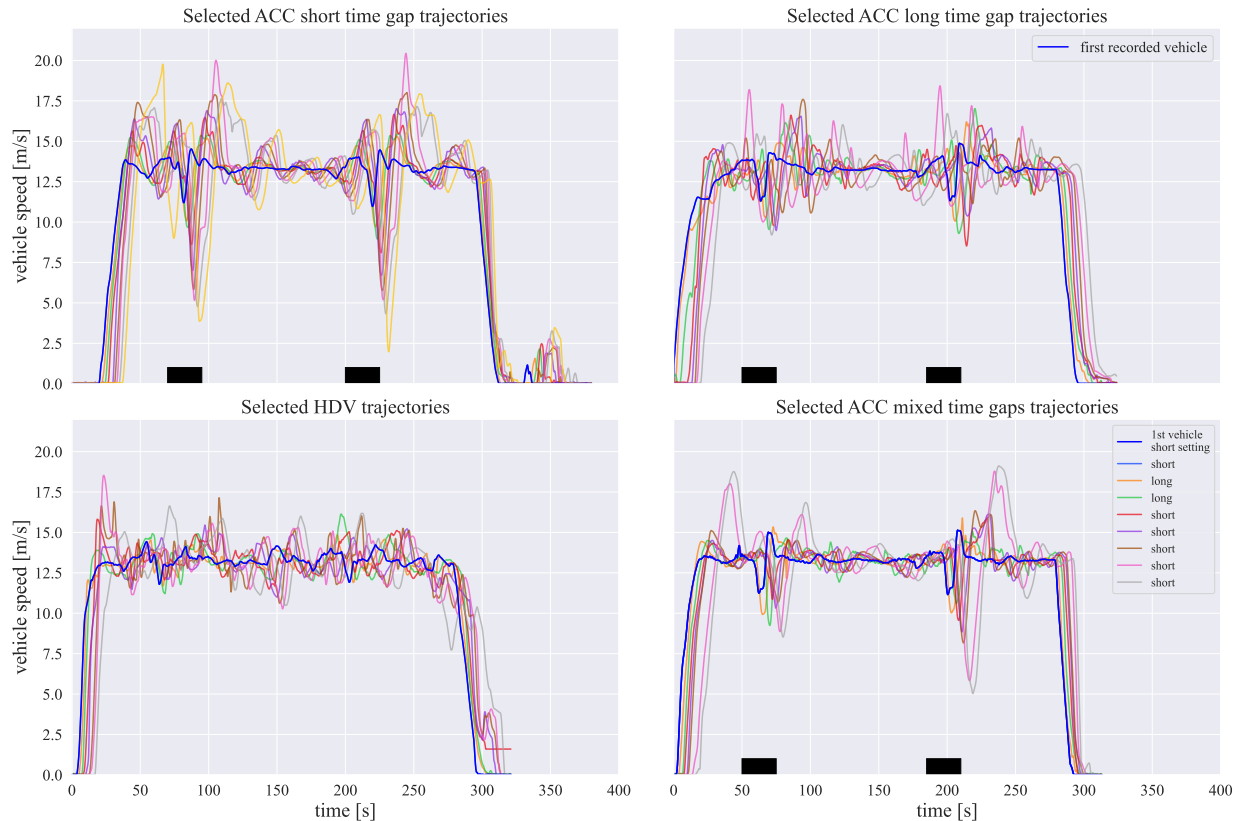


Figure 2. Selected platoons for the engine experiment. In the case of the short time gap platoon, the trajectory after $t=300$ s is not used. The period highlighted in black corresponds to the triggering event described in the subsection "Identifying the event."

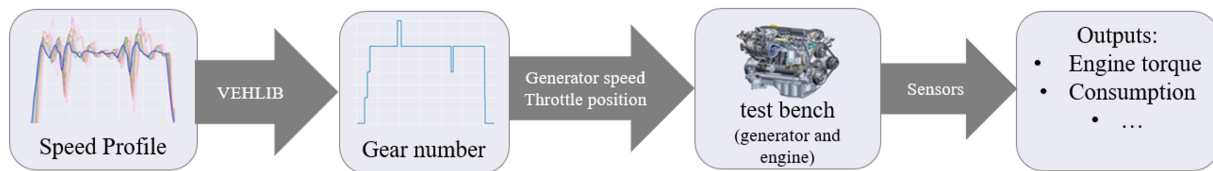


Figure 3. Protocol used to obtain consumption data using the engine. Each arrow corresponds to the execution of either a simulation tool or the execution of the hardware in a loop engine.

the vehicle's speed. This system is detailed in (26, 27). Figure 3 presents a global process overview.

Before launching the experiment and after each break, a warm-up cycle was imposed on the engine. The goal was to avoid a situation where the engine would consume more due to cold components. Before each measurement, the system was set in control mode to impose speed profiles. Then, we started the engine and ensured that it was not cold. When the engine stabilized at its idle speed of around 750 rotations per minute (values of this stabilization speed range from 730 to 780 rotations per minute), we launched the measurement system, and immediately after, we imposed the speed profile. After each experiment, we saved the following

measurements: time, speed, gearbox position, fuel rate, and fuel density. Each output was saved at a 10 Hz rate (the real-time loop runs at 100kHz). To ensure that the results are not dependent on the engine conditions, each trajectory was tested three times in the engine.

After experimenting with all the trajectories in the engine, we compared the global speed profiles of the initial data and the speed generated by the engine. For example, Figure 4 shows the speed profile from the original data compared with the engine's speed generated for the 6th vehicle of the long time gap ACC platoon.

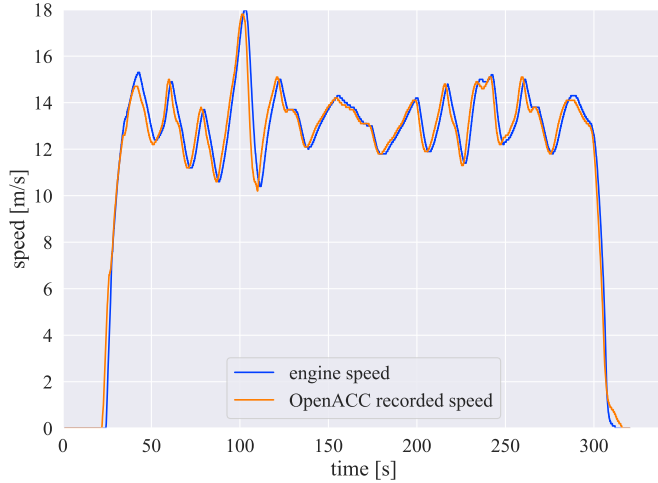


Figure 4. Comparison of the engine generated speed and the OpenACC recorded speed. The trajectory corresponds to the sixth vehicle of the long-time gap ACC platoon. The results are similar for all reproduced trajectories.

Experimental results

Consistency of the engine's results Before examining the physical meaning of our results, we checked that the engine results from one repetition to another are similar. Small fluctuations from one experiment to another are expected because the value of the engine speed at stabilized idle speed can slightly change between repetitions. To study these fluctuations, we calculated the mean consumption per 100 km during the entire cycle for each recorded experiment using the following conservation law:

$$consumption_{100\ km} = 100 * \frac{\int_{t_0}^{t_{max}} F_r(t) dt}{\int_{t_0}^{t_{max}} v(t) dt} \cdot \frac{1}{F_d} \quad (1)$$

where $F_r(t)$ is the fuel rate at time t , F_d is the mean value of the fuel density during the measurement, and $v(t)$ is the vehicle speed at time t .

We then compare this consumption with the mean consumption for the three repetitions for the same trajectory by computing the relative distance between the mean value of the three repetitions and the individual value of each repetition. The mean difference of the absolute value between measurements is 0.84 % (median = 0.67 %). The maximal distance between one individual measurement and the corresponding mean is 0.17L/100km, corresponding to a three % difference. The results show that the differences between measurements are small enough to be confident in the measurement process.

Consumption results Figure 5 shows the consumption results in litres per 100 km for each repetition versus the position in the platoon. A different colour represents each platoon type.

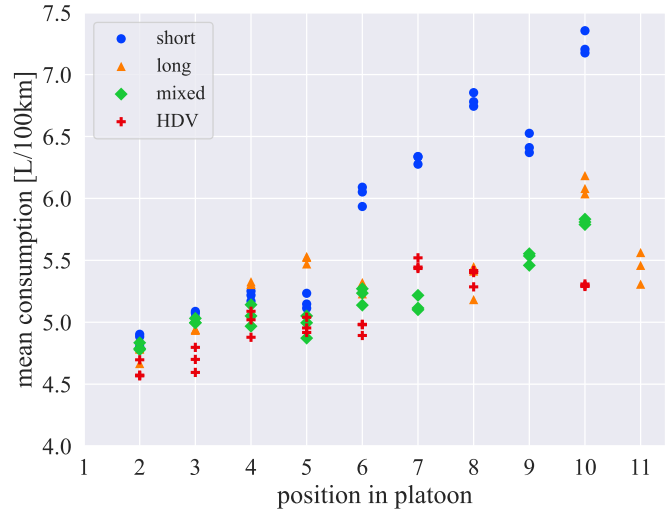


Figure 5. Scatter plot of the consumption of each tested trajectory by the position in the platoon. Each dot corresponds to one repetition. The colour indicates the platoon type.

The first observation is that the consumption increases with the position in the platoon, regardless of the platoon type. However, the increment seems higher for the short time gap platoon than the other platoons. Before the 6th vehicle position, there is no clear overconsumption from one platoon to another as the vehicle that consumes the most is either the short-time gap platoon vehicle (positions 2 and 3) or the long-time gap platoon vehicle (positions 4 and 5). From the 2nd to 4th position in the platoon, the consumption difference between the measurement with the highest consumption and the one with the lowest consumption is lower than or equal to 0.5L/100km. However, after the 6th vehicle position, the vehicles belonging to the short time-gap platoon consume at least 0.5 L/100km more than the vehicles belonging to any other platoon. The difference between the measurement with the highest consumption and the one with the smallest consumption is equal to or higher than 0.7L/100 km. We observe two outliers in those results: the 9th vehicle in the short time gap platoon and the 11th in the long time gap platoon. They tend to consume less than the previous vehicle, even if they are at the end of the platoon.

This is the consequence of the specific speed profiles of those two vehicles, showing no overreaction compared to their previous vehicles (see the corresponding vehicles' trajectories in Figure 2).

The results show that, in the case of five vehicles or less, we cannot identify any difference in consumption between platoon types. However, if their position in the platoon is equal to or larger than six, then the short time gap ACC vehicles tend to consume more than the HDV. For the vehicles belonging to the other types, there is no clear correlation between the position in the platoon and the difference in consumption compared with the HDV. The scatter plot

indicates a potential linear relation between consumption and the position in the platoon. This linear relation rate differs from one type of platoon to another.

Linear mixed-effect model We then test the hypothesis of a linear relation between the position within the platoon and the consumption for each platoon type. We are interested in detecting differences in impact across platoons. For each trajectory, we collected three repetitions in the test-bench experiment. To capture potential correlations between repetitions, we estimated a linear mixed-effect model. The linear mixed-effect model equation is as follows:

$$\begin{aligned}
 Y = & \alpha + \beta \cdot \text{position}_{HDV} \\
 & + (\alpha + \alpha_{long}) + (\beta + \beta_{long}) \cdot \text{position}_{long} \\
 & + (\alpha + \alpha_{mixed}) + (\beta + \beta_{mixed}) \cdot \text{position}_{mixed} \quad (2) \\
 & + (\alpha + \alpha_{short}) + (\beta + \beta_{short}) \cdot \text{position}_{short} \\
 & + \gamma + \epsilon
 \end{aligned}$$

α is the intercept for the HDV platoon used as the model's reference. β is the slope of the HDV platoon. $\alpha + \alpha_i$ is the intercept for one ACC platoon (i is the type of platoon), β_i is the slope for one platoon, γ captures the impact of the trajectory-specific error term taken from a normal distribution with mean zero and standard deviation μ , ϵ captures the effects of the observation-specific error term taken from a normal distribution with mean zero and standard deviation κ .

We perform a likelihood ratio test to understand if the trajectory-specific error term had a significant effect. The obtained p-value is 4.5×10^{-24} . The result shows that the observations significantly correlate across repetitions for the same trajectory (see table 2).

The long-time gap platoon is used as a reference category. If we compare the HDV results of the confidence interval of the β values with the mixed and HDV platoons, we see that there is no significant difference. This shows that the HDV is not significantly different from the mixed or long-time gap platoon regressions. Conversely, the same table 2 shows that the confidence interval of the short time gap β does not overlap with any of the other regressions. This shows that the parameter is significantly different compared to the three others.

Figure 6 presents the regression model and the confidence interval estimated with the bootstrap method. It shows that after the fifth vehicle in the platoon, the confidence interval for the short-time gap platoon does not overlap with the confidence intervals of any other platoon type.

In conclusion, a platoon that only contains ACC vehicles with a short time gap of at least five vehicles consumes significantly more than any other type of platoon of the same size. This finding agrees with previous studies highlighting the relation between short time gap setting and the magnitude

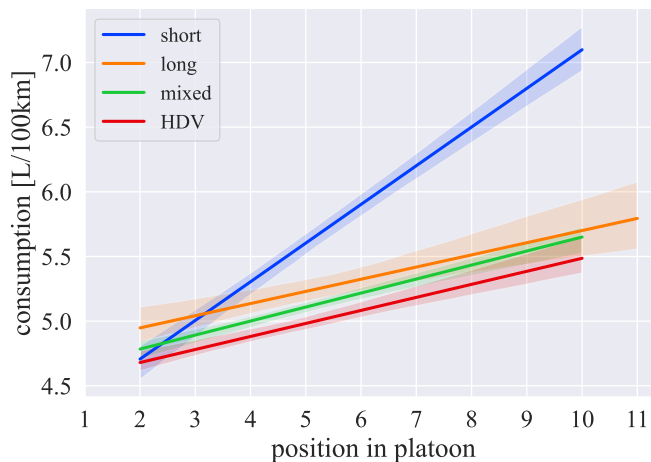


Figure 6. Linear mixed effect model that links the consumption as a function of the position in the platoon for each different platoon type. The solid line indicates the marginal mean. The coloured ribbon shows the 95% confidence interval computed using the bootstrap method.

of string instability (28). Indeed, vehicles in a short time gap setting ACC platoons tend to accelerate more due to considerable instability. As a consequence, the amount of fuel needed increases. These findings are based on data collected in a test-track experiment, where a significant deceleration of the leader triggered string instability. To have an overview of the overconsumption of ACC, we need to analyze how often such events might happen in actual traffic conditions.

Event occurrence based on trajectory dataset

Selection of the events

The results in the test bench experiment showed that, in the case of platooning, short time gap ACC vehicles lead to significant overconsumption when they are the only type of vehicle in the platoon. In short time-gap platoon trajectories, two deceleration-acceleration events by the leader lead to a string instability as the one described by Wilson (15). The deceleration-acceleration events between the first and the ninth follower lead to an eight m/s minimal speed difference in the first event and a ten m/s speed difference in the second event. Such deceleration-acceleration events are not seen in any other trajectory. This leads some authors to suppose that the deceleration-acceleration patterns that produce the string instability are also the event creating the overconsumption (14). The work presented in this part of the paper aims to identify whether the events we studied with the engine test bench test are frequent in real-world traffic.

In the OpenACC data used in the previous part, the leader trajectories were recorded at 1Hz and were noisy due to the sampling rate. Therefore, we used the first follower

Table 2. Results of the linear mixed-effect model that links the consumption as a function of the position in the platoon for each different platoon type. The final log-likelihood is obtained using the ML estimation method. The parameters are estimated using the REML method. The results are displayed with the HDV platoon used as a reference category for intercept and slope.

Model statistics							
No. Observations	99						
No. Groups	33						
Group size	3						
Final log-likelihood:	72.16						
Parameter	value	Std. Err.	z	$P > z $	[0.025	0.975]	
Slope (reference HDV)	0.101	0.031	3.211	0.001	0.039	0.162	
Slope long platoon	-0.007	0.040	-0.166	0.869	-0.086	0.073	
Slope mixed platoon	0.008	0.043	0.174	0.862	-0.077	0.092	
Slope short platoon	0.198	0.042	4.670	0.000	0.115	0.281	
Intercept(reference HDV)	4.478	0.193	23.192	0.000	4.100	4.857	
Intercept long platoon	0.281	0.261	1.079	0.281	-0.230	0.792	
Intercept mixed platoon	0.089	0.270	0.330	0.741	-0.439	0.617	
Intercept short platoon	-0.370	0.269	-1.377	0.169	-0.897	0.157	
Group Variance	0.048	0.236					
Residuals	0.0048						

speed profile to define the event leading to string instability and overconsumption. Looking at the speed profiles, we noticed that the string instability is always preceded by a deceleration-acceleration with a $\Delta v > 2.5\text{m/s}$ of the first follower. We define this pattern as the triggering event that leads to string instability and overconsumption, as shown in (14). The triggering event is defined when three conditions are met:

- The follower shows a higher acceleration and deceleration compared to the leader;
- The deceleration leads to a reduction of the first follower speed of 2.5 m/s over a few seconds, immediately followed by an acceleration of 100 % to 150 % more important than the deceleration;
- This pattern is then followed by a string instability that involves the entire platoon.

We observe two events corresponding to the above definition for each first follower trajectory in each ACC platoon within the OpenACC subset we used (see periods highlighted in black in Figure 3).

Mathematically, we can define the above triggering event as follows. Let E be a deceleration-acceleration event and E^* be the set of the triggering events that correspond to the description underneath (note that numerical values are based on the observation of the data):

$$E \in E^* \Leftrightarrow \exists t_0, t_1, t_2 \quad (3)$$

where

- $t_2 - t_0 < 15\text{s}$
- $v(t_1) = \min(v(t)) \forall t \in [t_0, t_0 + 100]$
- $v(t_2) = \max(v(t)) \forall t \in [t_0, t_0 + 100]$

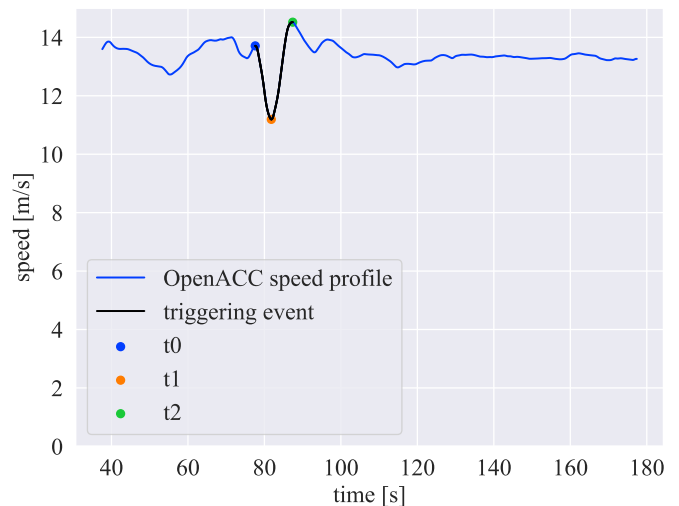


Figure 7. One example of the triggering event that led to the string instability wave. t_0 indicates the beginning of the event, t_1 indicates the time of the minimal speed within the event, and t_2 indicates the end of the event.

Figure 7 shows an example of a triggering event and illustrates the mathematical definition.

We selected the events corresponding to the above definition in the three ACC platoons' first follower trajectories used in the engine test bench. On average, we have a triggering event with a deceleration phase that leads to $\Delta v_1 = -2.4\text{m/s}$ speed difference followed by an acceleration phase with a $\Delta v_2 = 3.5\text{m/s}$ speed difference and a total duration of $\Delta T = 11.6\text{s}$.

The following section will only consider the triggering events that lead to string instability. That corresponds to the six triggering events related to the ACC platoons.

Trajectory dataset description

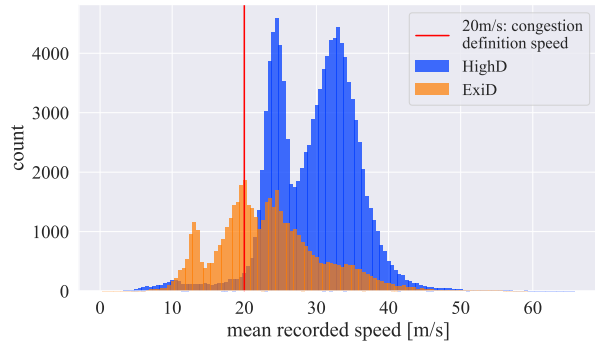


Figure 8. Histogram of the mean recorded speed for each vehicle in HighD and ExiD datasets. Each bar corresponds to the mean speed of one vehicle trajectory within one dataset or the other. The red line is the limit we set to consider that a trajectory belongs to a congested scene.

We use the trajectories in the HighD (21) and ExiD datasets (22) to determine how often the triggering events described in the above section happen in real traffic. These two datasets were collected in German Autobahns using drones by a team from Ika and the University of Aachen. They captured highway scenes in the two directions on 400m sections. The trajectories were extracted from the video recordings using a neural network. 9.63×10^8 hours of trajectories were collected. The datasets include records of both free-flow and congested traffic conditions. The data contain each vehicle's timestep, position, speed, acceleration, current lane, time and distance gap, and time to collision. Trajectories were recorded on motorway sections near Koln and Dusseldorf. While HighD trajectories were recorded on motorway straight sections, ExiD trajectories were collected in highway merging and diverging geometries. Figure 8 presents the mean speed distribution of each vehicle record of the two datasets.

As major acceleration and deceleration are very uncommon in the case of free-flow traffic records, we decided to limit our comparison to the congested traffic conditions in these two datasets. We define a traffic condition as congested if the mean speed is under 20 m/s, corresponding to a 45 % speed reduction compared to the recommended speed. After applying the condition on the mean speed, we are left with two HighD records to explore out of 59 and 20 ExiD records out of 54. The mean rate of the selected scenes varies from 4.6m/s to 17m/s. These scenes record $1.59 \times 10^8 h$ of total travel time. Using these records, we determined the percentage of time when a triggering event occurred.

Events identification result

We determine how often such deceleration-acceleration, like the ones in the OpenACC triggering events, happens in congested traffic by analyzing the speed profiles in the

selected scenes. For each speed profile, we compare on a period of $[t_0, t_0 + 15 \text{ s}]$ the dynamic time warping (DTW) distance (24) between each triggering event and the speed profile during the period. We then compare the mean DTW distance between the HighD speed profile and each of the six *triggering events* (as presented in) to the reference distance, calculated based on the mean distance between the six *triggering events* as shown in section . We use a moving window of a 15s length as described in Figure 9.

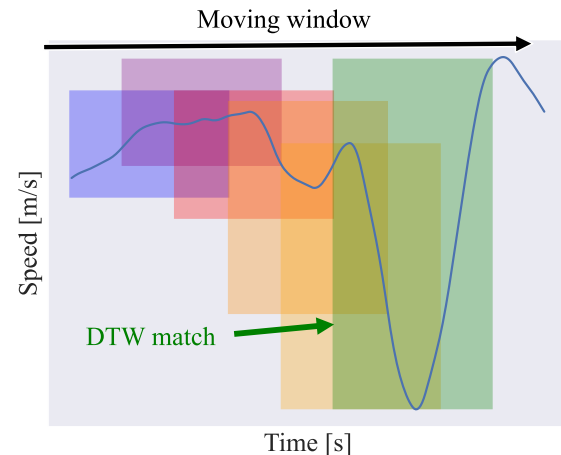


Figure 9. Used algorithm to detect if a 15s sample of the speed profile of one vehicle taken from HighD or ExiD is similar to the *triggering event*. The size of the moving window is 15s, and the displacement for each iteration is 2s.

The method presented in Figure 9 gives us the ratio between the temporal periods when a triggering event happens and the total travel time.

We apply this method to the 22 records corresponding to the congested situations. We found 12,686 *h* out of $1.59 \times 10^8 h$ corresponding to triggering events. This leads to a ratio of 7.98×10^{-5} between the total duration of the recordings and the cumulated duration of all the triggering events. This highlights that such events are infrequent within motorway traffic.

We compared the findings to previous studies to understand the impacts on global traffic consumption. According to a study (29) that used original NGSIM data (30), the mean consumption in congestion in a motorway with only HDV is 14.7 L/100km (keep in mind that the values are taken from a 2008 study and might be lower nowadays). We supposed that the mean consumption value corresponds to the consumption of the first follower. Note that this is an overestimation. The first vehicle of a platoon will necessarily consume less than the average consumption as it is not subject to triggering. We extrapolated the consumption of an ACC platoon, supposing that from one vehicle in a platoon to another vehicle, the ratio $\frac{Consumption_{veh_i}}{Consumption_{veh_{i-1}}}$ is the same as in

our engine bench experimentation results. We then supposed that each vehicle was part of a 10-vehicle ACC platoon and that each vehicle had a short time-gap setting, a very pessimistic hypothesis in terms of consumption. Even with such a pessimistic hypothesis, the percentage increase in fuel consumption equals $1.7 \times 10^{-5}\%$.

Discussion and conclusion

In this paper, we studied the impact of ACC vehicles on consumption. To do so, we used a two-step framework. First, we studied ACC overconsumption in the case of platooning using OpenACC data (8) in an engine bench. Second, we determined what event could cause such overconsumption and computed how often such an event happens in real traffic using HighD and ExiD datasets.

The results of the engine bench show that ACC vehicles with a short time gap setting consume more than HDV in the case of platoons with five or more vehicles. The difference in consumption increases with the length of the platoon. However, the event we identified as the origin of overconsumption (i.e., an acceleration-deceleration triggering event) is too rare to produce any noteworthy overconsumption globally, as it occurs 0.08 % of the time. If the platoon consumption results are observed in real traffic, the global overconsumption will be only $1.7 \times 10^{-5}\%$.

Notably, the impact of the position in the platoon on consumption is similar between ACC with long or mixed time gaps platoons and HDV. The mixed platoon comprises three short time gap ACC vehicles, two long time gap ACC, and three short time gap ACC. We could have expected, given this composition, that the consumption of the vehicles within this platoon would have been higher than the ones of the long time gap platoon. Yet, this is not the case. Adding two long time gap ACC in a platoon mainly composed of short time gap ACC is sufficient to reduce the consumption to the one of a platoon entirely consisting of long time gap ACC.

Those results highlight that the main issue for overconsumption in ACC traffic is the long platoons of short time gap setting vehicles.

We tried to find a potential link between vehicle model and impact on consumption. However, we could not clearly identify differences between the responses of different makes and models. This element should be further investigated in future research as we could not address it due to the experimental design.

The findings in this study must be interpreted with caution. We assumed that ACC vehicles consume more when facing string instability and consume the same as HDV vehicles in any other situation. Since this scenario presents the most probable circumstance for witnessing a brutal acceleration of ACC, it's likely the sole instance. The data were collected on a single test track, which might limit the generalizability of the findings. The part of the OpenACC dataset we used was collected on a test track with curves, while the

HighD and ExiD dataset was collected on straight segments of the motorway mainline. As the primary use case of ACC is the motorway mainline, this is representative of the traffic situations where ACC vehicles are most often used nowadays. However, if ACC usage were extended to motorway ramps and rural roads with curves, we might observe a different proportion of triggering event occurrence. Concurrently, the penetration rate of ACC within the HighD and ExiD datasets is expected to be 5%. In case of a global increase in the penetration rate, the occurrence of triggering events might change.

The engine in the test bench experiment was less potent than the engines in the vehicles used to collect the speed profiles in the test track (12). This means that the test bench's engine needed more energy to reach the same torque, leading to overestimating the consumption values. However, the comparison across experimental conditions is expected to be similar with a different engine.

The results have important implications for practice and future research. Since ACC platoons consume more than HDV only when all ACC vehicles use a short time gap setting, a specific regulation could be introduced to increase the minimal time gap one can choose in certain traffic situations. Furthermore, a policy to reduce the size of the short time gap platoons on the road as much as possible could also help avoid such situations. To do so, we could create an algorithm that produces a large time gap after two harsh decelerations. This would break the long platoon formation and avoid overconsumption.

Beyond the consumption impact, the string instability observed in OpenACC data is a potential issue for traffic safety. Such an event produces harsher and harsher deceleration within the platoon. Therefore, it can trigger a rear-end collision in extreme cases. Some studies that analyzed trajectories right before crashes in motorways (31) have shown that a deceleration harsher than $-2.7m/s^2$ in a congested section led to an increase in the crash probability (1 crash every 88 harsh braking recording during a one hour period in one kilometre). In the OpenACC data, we observed three vehicles that execute such a deceleration in the short time gap and mixed time gap platoon and one vehicle in the long time gap platoon. In the case of mainly HDV traffic, we have a 1/1250 probability (by per 15-second intervals) of a triggering event. This means that each vehicle in a congested situation for a period of 15 minutes has a 1/20 probability of overreacting and executing a triggering event. However, with the increase in ACC penetration rate, this value might increase, resulting in a higher crash probability. Future work will focus on assessing the impact of ACC on traffic safety.

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Author Contribution Statement

The authors confirm their contribution to the paper as follows:

- Study conception and design: Christine Buisson, Silvia Varotto, and Thibault Charlottin;
- Data selection for the experimentation: Thibault Charlottin, Bruno Jeanneret, Christine Buisson, and Silvia Varotto;
- Engine bench test experimentation: Bruno Jeanneret, Thibault Charlottin, and Sylvain Gillet;
- Analysis and interpretation of engine bench results: Thibault Charlottin, Bruno Jeanneret, Christine Buisson, Silvia Varotto;
- Analysis of event prevalence in real-life traffic data: Thibault Charlottin, Christine Buisson, and Silvia Varotto;
- Data processing and figure creation: Thibault Charlottin;
- Draft manuscript preparation: Thibault Charlottin, Christine Buisson, and Silvia Varotto.

All authors reviewed the results and approved the final version of the manuscript.

Code availability

The used code is available at <https://github.com/thibault-charlottin/ACC-platoon-fuel-consumption>; instructions to get HighD data from Aachen University are presented in the ReadMe file. This file also explains how to download the VEHLIB software and run it to replicate using a simulation tool, the results obtained in the engine bench.

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