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# FUEL CONSUMPTION OF ADAPTIVE CRUISE CONTROL PLATOONS: BENCH EXPERIMENTS AND DATA-DRIVEN ESTIMATION FOR REAL TRAFFIC –Manuscript Draft

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## ► To cite this version:

Thibault Charlottin, Silvia Varotto, Bruno Jeanneret, Sylvain Gillet, Christine Buisson. FUEL CONSUMPTION OF ADAPTIVE CRUISE CONTROL PLATOONS: BENCH EXPERIMENTS AND DATA-DRIVEN ESTIMATION FOR REAL TRAFFIC –Manuscript Draft. Transportation Research Board Annual meeting, Jan 2024, Washington DC, United States. hal-04659403

**HAL Id: hal-04659403**

**<https://hal.science/hal-04659403v1>**

Submitted on 23 Jul 2024

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## TRB Annual Meeting

# FUEL CONSUMPTION OF ADAPTIVE CRUISE CONTROL PLATOONS: BENCH EXPERIMENTS AND DATA-DRIVEN ESTIMATION FOR REAL TRAFFIC

--Manuscript Draft--

<b>Full Title:</b>	FUEL CONSUMPTION OF ADAPTIVE CRUISE CONTROL PLATOONS: BENCH EXPERIMENTS AND DATA-DRIVEN ESTIMATION FOR REAL TRAFFIC
<b>Abstract:</b>	<p>Vehicles equipped with adaptive cruise control (ACC) systems are expected to improve traffic safety and decrease fuel consumption. Recent 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. Using HighD and ExiD records, we detect if the events leading to overconsumption often happen in traffic. 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. 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, it is too rare in traffic to impact global fuel consumption.</p>
<b>Manuscript Classifications:</b>	Operations; Traffic Flow Theory and Characteristics ACP50; Traffic Flow; Vehicle-Highway Automation ACP30; Automated Vehicles
<b>Manuscript Number:</b>	TRBAM-24-00774
<b>Article Type:</b>	Presentation and Publication
<b>Order of Authors:</b>	<p>Thibault Charlottin</p> <p>Silvia Varotto</p> <p>Bruno Jeanneret</p> <p>Sylvain Gillet</p> <p>Christine Buisson</p>
<b>Additional Information:</b>	
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1 **FUEL CONSUMPTION OF ADAPTIVE CRUISE CONTROL PLATOONS: BENCH**  
2 **EXPERIMENTS AND DATA-DRIVEN ESTIMATION FOR REAL TRAFFIC**

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16 Word Count: 6156 words + 2 table(s) × 250 = 6656 words

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23 Submission Date: July 28, 2023

Under Review

**1 ABSTRACT**

2 Vehicles equipped with adaptive cruise control (ACC) systems are expected to improve traffic  
3 safety and decrease fuel consumption. Recent studies have shown that ACC leads to string in-  
4 stability in the case of platooning and can therefore result in higher energy needs compared to a  
5 platoon of human-driven vehicles (HDV). However, the impact of the ACC on fuel consumption  
6 in the case of platooning and the global impact of ACC overconsumption in traffic is not known  
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8 data and traffic records. In this study, we inject the speed profiles of ACC and HDV platoons that  
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12 that only ACC platoons of six or more vehicles with a short time-gap setting consume more than  
13 HDV platoons. The results on HighD and ExiD show that such an event happens once out of 1250  
14 if we divide the time into steps of 15 seconds. This shows that even if overconsumption exists in  
15 specific cases, it is too rare in traffic to impact global fuel consumption.

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

## 1 INTRODUCTION

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

8 Some recent studies have collected ACC platooning trajectories during experiments (7,  
9 8). Further studies based on these data have analyzed the impact of ACC on road capacity by  
10 creating fundamental diagrams (9, 10) and have found that ACC can decrease road capacity up  
11 to 25% for a 100 ACC penetration rate (10). Other studies (8, 11–13) have shown that ACC  
12 vehicles in a platoon tend to create string instability (14). The system generates a deceleration  
13 overshooting followed by an acceleration overshooting that propagates to the other vehicles in the  
14 platoon, increasing in magnitude. This deceleration-acceleration overshooting is not observed in  
15 human-driven vehicles (HDV) platoons following the same trajectory (13) and might harm both  
16 traffic safety and fuel consumption.

17 ACC fuel consumption has been studied since the beginning of ACC commercialization.  
18 Some early studies determined that ACC, depending on its algorithm and the chosen setting, would  
19 consume between 8 and 28 % less fuel (15). However, the models used were based on assumptions,  
20 not on experimental data with ACC vehicles. Other studies have been focusing on developing eco-  
21 driving algorithms for ACC systems to reduce fuel consumption (16). Some models (13, 17) were  
22 developed based on data collected in ACC platoon experiments (7), and have found a link between  
23 the string instability produced by ACC platoons and an increase of the energy that the car needs to  
24 progress compared with HDV platoons (18).

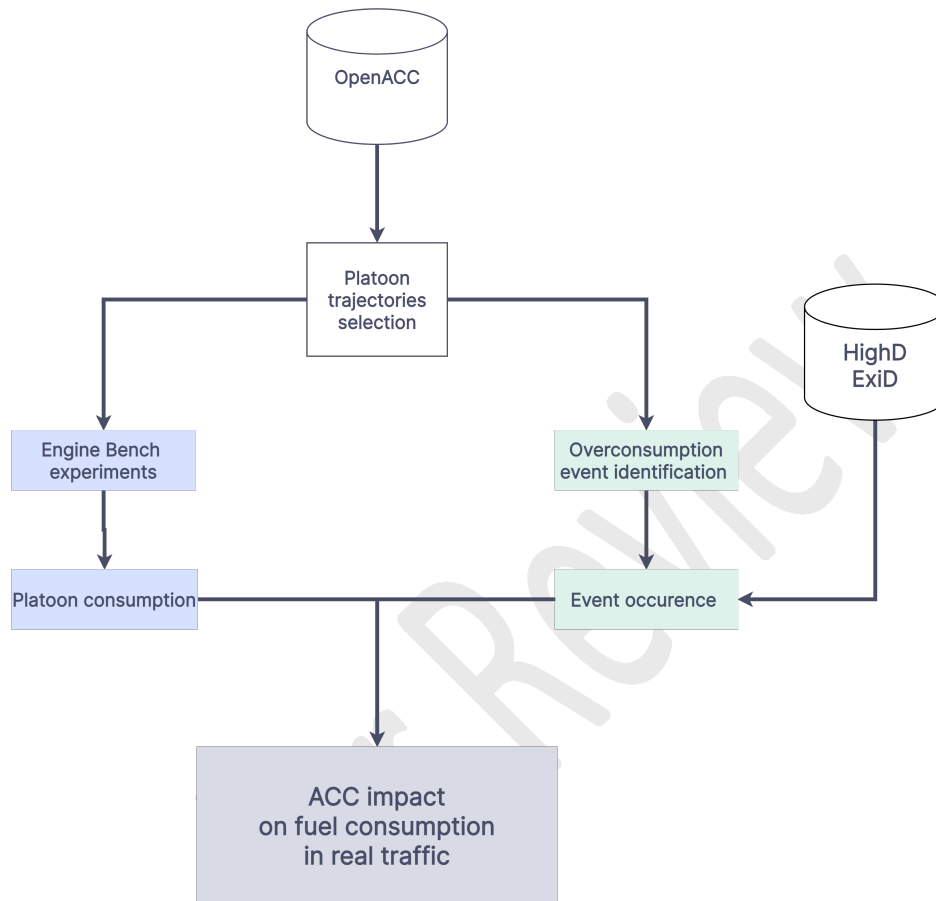
25 String instability can appear only when vehicles are in a platooning formation. In any other  
26 situation, the time gap is large enough for at least one ACC vehicle to switch back to cruise control  
27 mode. This would cut the wave of overshooting and then limit the extent of string instability. This  
28 means that if the ACC vehicles are not in platooning formations, they will drive at a constant speed.  
29 The constant speed is the situation where the vehicle consumes the least (19). This suggests that  
30 ACC vehicles have a negative impact on fuel consumption if and only if they are in a platooning  
31 formation.

32 In summary, previous studies have shown that ACC vehicles, in case of platooning, tend  
33 to overaccelerate and that it is correlated with string instability. As they are doing so, their need  
34 for energy increases. However, the issue of fuel consumption of ACC platoons, which is not  
35 necessarily a linear function of energy need, has never been addressed.

36 This paper aims to experimentally determine the consumption differences between ACC  
37 vehicles and HDV at a global traffic scale. First, this will be done using platoon trajectories as it  
38 is the only situation where we could observe significant differences with a regular cruise control  
39 vehicle. Then, a large-scale traffic dataset will be analyzed to identify how often speed fluctuations  
40 like the ones observed in platoons happen in real traffic.

41 Figure 1 shows a global overview of the framework. First, we select trajectories of ACC  
42 and HDV in a platooning experiment on a test track to pick up the platoons with the most similar  
43 leader profiles. To do so we use OpenACC data (7). Second, we inject the trajectories in an engine  
44 test bench to determine the impact of automation on consumption in the case of platooning. Those  
45 two steps 1 and 2 are described in the next part. Third, we identify the specific events that might

- 1 trigger a difference in consumption within a trajectory. Finally, we examine how often these events
- 2 might happen in real-life traffic based on traffic datasets. This part is done using HighD and ExiD
- 3 datasets (20, 21). Steps 3 and 4 are described in the third section.



**FIGURE 1:** Flowchart of the study. Blue indicates the step used to determine the consumption of ACC platoons. Green represents the step to determine if the used trajectories injected in the bench during the part step are frequent or not.

#### 4 FUEL CONSUMPTION IN AN ENGINE BENCH EXPERIMENT

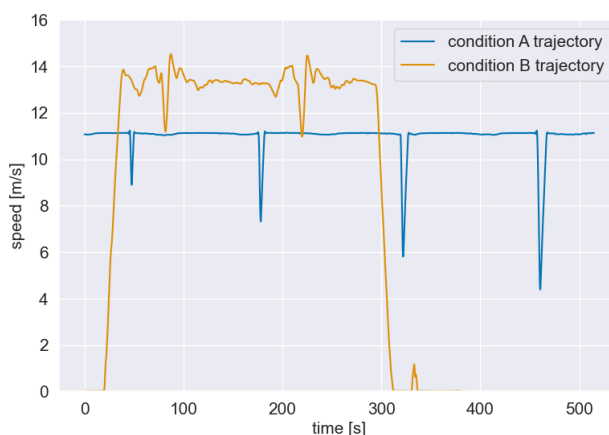
##### 5 Data selection

6 Speed and acceleration profile, road gradient, vehicle characteristics, and local weather influence  
 7 fuel consumption. As we don't expect ACC and HDV vehicles to show the same response to a  
 8 similar event, we have to analyze vehicles following a platoon leader with a similar speed profile  
 9 in the same environment.

10 These two prerequisites are met by datasets collected in the experiment on the Astrazero  
 11 test track during the OpenACC campaign by the JRC team (7, 11). The goal was to analyze the  
 12 impact of long platoons of ACC vehicles (*i.e.*, 10 to 12 vehicles). Several ACC vehicles and  
 13 HDV settings were tested with the same leader trajectories. Vehicles were following each other  
 14 in a platoon formation. The data were collected at a 10Hz rate through sensors placed inside the  
 15 vehicles. The vehicles were driven either manually or with the ACC activated. When the ACC

1 system was activated, several time gap settings were tested (short, long, and medium time gaps).  
 2 The shorter the time gap, the more reactive the response of the following vehicle. Two different  
 3 experimental conditions were tested as follows (Figure 2):

- 4 • Condition A: the leader drove at a constant speed except for short periods when he/she  
 5 brutally decelerated and accelerated to get back to its initial speed;
- 6 • Condition B: all vehicles started at a standstill, and the leader imposed a speed profile.  
 7 The leader speed variations are only based on the leader driver’s reactions to the road  
 8 geometry. In this condition, as the leader was not present in the data, we used the speed  
 9 profile of the first follower as our reference.



**FIGURE 2:** The two experimental conditions that exist within the OpenACC dataset

10 The comparison of the two experimental conditions has shown that condition A leads to  
 11 emergency braking, which rarely happens in real traffic on freeways. We decided to focus on the  
 12 trajectories in experimental condition B as their deceleration-acceleration phases are more likely  
 13 to be observed in real traffic. The goal is to select the HDV and ACC trajectories with the most  
 14 similar leader speed profile.

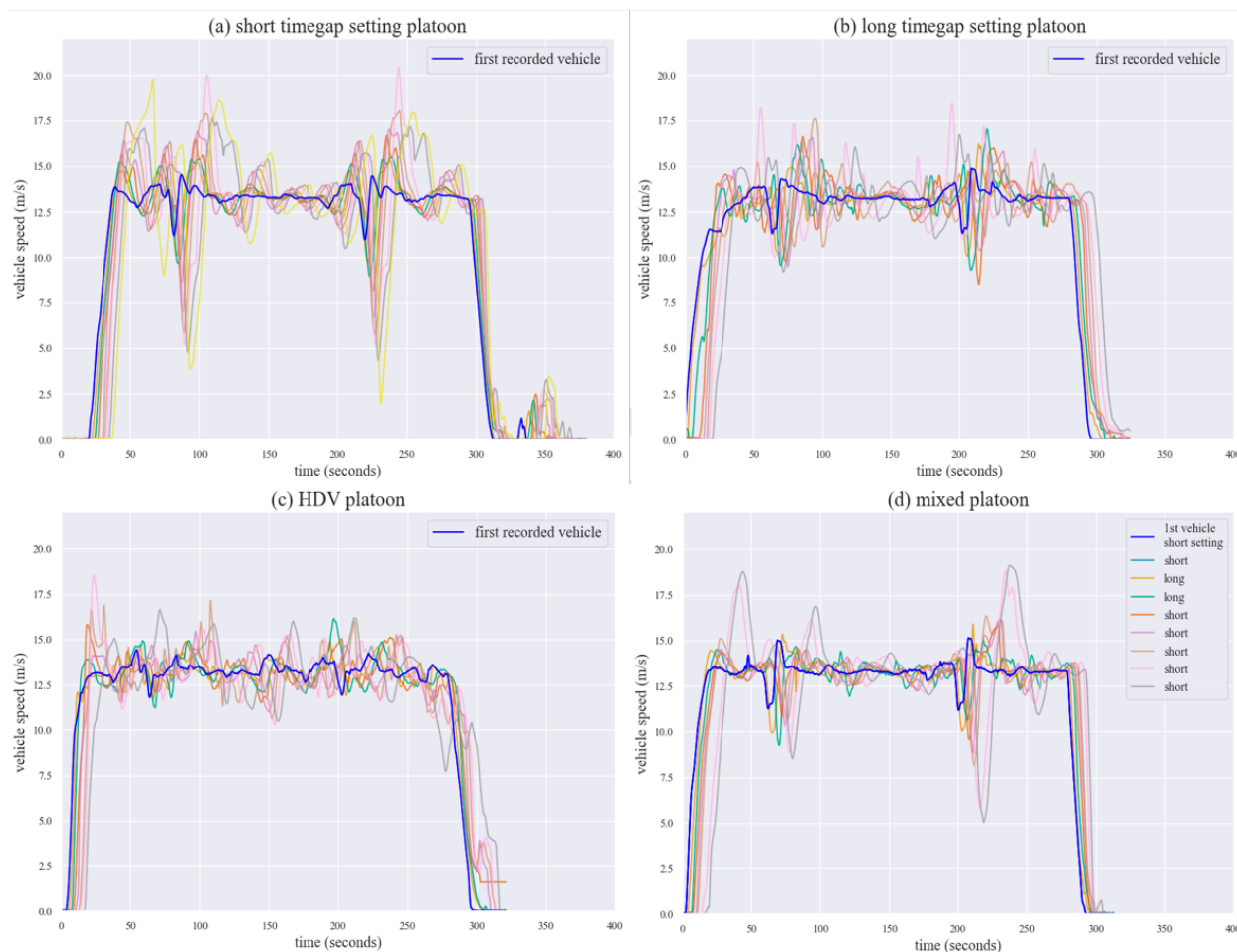
15 We first separated the platoons into groups based on their mean speed ( $8m/s$ ,  $11m/s$ ,  
 16  $14.5m/s$ , and  $17.5m/s$ ) and their setting (HDV, ACC with short time gap setting, ACC with long  
 17 time gap setting or ACC platoons with different settings from one vehicle to another). For each  
 18 group (same mean speed and setting), we compared all the first recorded trajectories and selected  
 19 the platoon with the most similar first-recorded trajectories. This first recorded trajectory corre-  
 20 sponds to the first follower, as the leader’s trajectory is not included in OpenACC.

21 To do so, we compute for each first-recorded trajectory the distance with every other first-  
 22 recorded trajectory that does not belong to the same platoon group<sup>1</sup> using the dynamic time-  
 23 wrapping algorithm (22). This allowed us to identify a platoon for each ACC setting with the  
 24 closest first-recorded trajectory, leading to the selection of four platoons. Figure 3 presents the  
 25 speed profiles. In all ACC trajectories, we notice two large deceleration-acceleration patterns.  
 26 These events are always followed by string instability according to Li and al. (12) and Ciuffo and  
 27 al. (13). In the case of short time gap platoons, the string instability is more important and leads to

<sup>1</sup>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

1 harsher decelerations and accelerations compared to the other trajectories. This shows that short  
 2 time gap ACC platoons tend to accelerate more than other ACC platoons or HDV platoons.

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



**FIGURE 3:** Selected platoons for the engine experiment. In the case of the short time gap platoon, events that occur after  $t=300s$  are not used.

## 9 Engine bench experiment

10 The principle of the real-time experiment consists in controlling a real engine in the bench while  
 11 simulating the driveline and the resistive force of the vehicle. The engine is from a Renault Kadjar  
 12 TCE130, and its characteristics are presented in table 1.

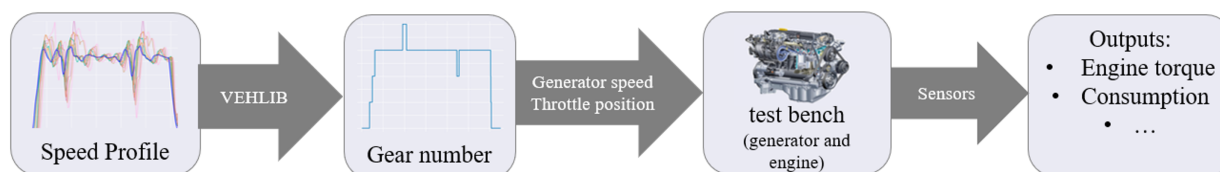
13 The engine follows the indicated instructions computed by the VEHLIB model, a Simulink  
 14 package created by the Université Gustave Eiffel (23). In detail, the models work in power hard-  
 15 ware in the loop mode: a simulated vehicle controller follows the desired speed by choosing the



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

**TABLE 1:** Hardware in the loop engine characteristics

1 correct gear number at each time step and sending a throttle value to the real engine controller. An  
 2 energetic vehicle model runs in the real-time processor and interacts with the bench. The VEHLIB  
 3 library is also used to interface data and the engine. Sensors placed all over the engine allow one to  
 4 record indicators such as engine torque, temperature, fuel consumption, and fuel density. Engine  
 5 torque is then re-injected in real-time into the VEHLIB model, which estimates the speed of the  
 6 vehicle. This system is presented in detail in (24, 25). Figure 3.2 presents a global overview of the  
 7 process.

**FIGURE 4:** Protocol used to obtain consumption data using the engine

8 Before launching the experiment and after each break, a warm-up cycle was imposed on  
 9 the engine. The goal was to avoid a situation where the engine would consume more due to cold  
 10 components. Before each measurement, the system was set in control mode so that speed profiles  
 11 could be imposed. Then we started the engine and ensured that it was not cold. When the engine  
 12 stabilized at its idle speed of around 750 rotations per minute<sup>2</sup>, we launched the measurement  
 13 system, and immediately after, we imposed the speed profile. After each experiment, we saved the  
 14 following measurements: time, speed, gearbox position, fuel rate, and fuel density. Each output  
 15 was saved at a 10 Hz rate<sup>3</sup>. To ensure that the results are not dependent on the engine conditions,  
 16 each trajectory was tested three times in the engine.

17 After experimenting with all the trajectories in the engine, we compared the global speed  
 18 profiles of the initial data and the speed generated by the engine. As an example, Figure 5 shows  
 19 the speed profile from the original data in comparison with the speed generated by the engine for  
 20 the 6th vehicle of the long time gap ACC platoon.

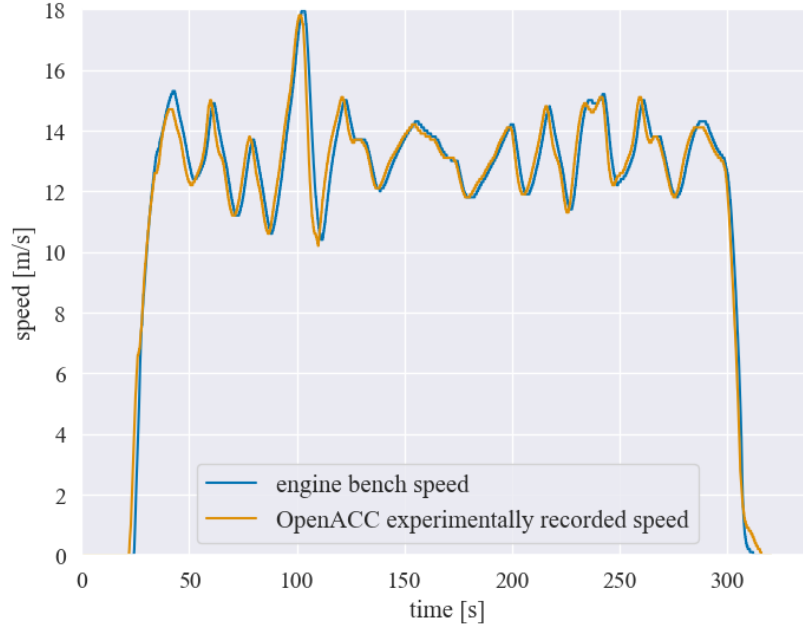
## 21 Experimental results

### 22 *Verifying that the engine produces consistent results*

23 Before examining the physical meaning of our results, we first checked that the engine results  
 24 from one repetition to another are the same. Small fluctuations from one experiment to another are  
 25 expected because the value of the engine speed at stabilized idle speed can slightly change between

<sup>2</sup>values of this stabilization speed range from 730 to 780 rotations per minute

<sup>3</sup>the real-time loop runs at 1kHz



**FIGURE 5:** Comparison of the engine generated speed and the OpenACC recorded speed. The trajectory corresponds to the 6th vehicle of the long time gap ACC platoon. The results are similar for all reproduced trajectories.

1 repetitions. To study these fluctuations, we calculated the mean consumption per 100 km during  
 2 the entire cycle for each recorded experiment using the following conservation law:

$$3 \quad consumption_{100 \text{ km}} = 100 * \frac{\int_{t_0}^{t_{max}} F_r(t) dt}{\int_{t_0}^{t_{max}} v(t) dt} \cdot \frac{1}{F_d} \quad (1)$$

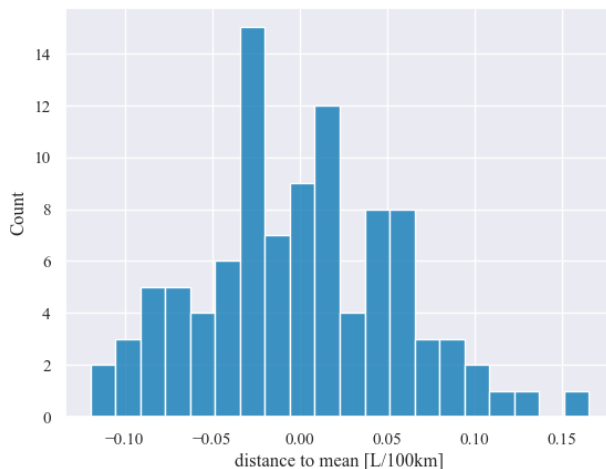
4 where  $F_r(t)$  is the fuel rate a time  $t$ ,  $F_d$  is the mean value of the fuel density during the measure-  
 5 ment, and  $v(t)$  is the vehicle speed at time  $t$ . We then compare this consumption with the mean  
 6 consumption for the three repetitions for the same trajectory. Figure 6 presents the histogram of  
 7 the difference in consumption for each measurement compared with the mean. To create it, we  
 8 computed the relative distance between the mean value of the three repetitions and the individual  
 9 value of each repetition.

10 The mean difference of the absolute value between measurements is 0.84 % (median = 0.67  
 11 %). The maximal distance between one individual measurement and the corresponding mean is  
 12 0.17L/100km, which corresponds to a 3 % difference. The results show that the differences from  
 13 one measurement to another are small enough to use all repetitions.

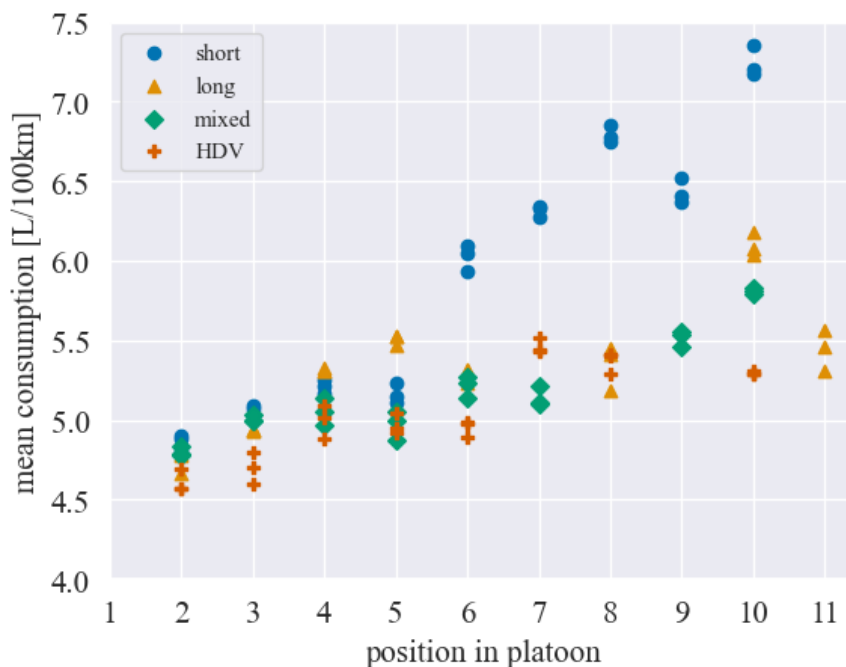
#### 14 *Consumption results*

15 Figure 7 shows the consumption results in liters per 100 km for each repetition versus the position  
 16 in the platoon. A different color represents each platoon type.

17 The first observation is that the consumption increases with the position in the platoon, no  
 18 matter the platoon type. However, the increment seems higher for the short time gap platoon than  
 19 the other platoons.



**FIGURE 6:** Histogram of the distance between the observed consumption of one repetition and the mean consumption of the three repetitions for every trajectory.



**FIGURE 7:** Scatter plot of the consumption results. The color indicates the platoon type.

1 Before the 6<sup>th</sup> vehicle position, there is no clear overconsumption from one platoon to  
 2 another as the vehicle that consumes the most is either the short time gap platoon vehicle (positions  
 3 2 and 3) or the long time gap platoon vehicle (positions 4 and 5). From the 2<sup>nd</sup> to 4<sup>th</sup> position in  
 4 the platoon, the consumption difference between the measurement with the highest consumption  
 5 and the one with the lowest consumption is lower than or equal to 0.5L/100km.

6 However, after the 6<sup>th</sup> vehicle position, the vehicles belonging to the short time-gap pla-  
 7 toon consume at least 0.5 L/100km more than the vehicles belonging to any other platoon. The  
 8 consumption difference between the measurement with the highest consumption and the one with

1 the smallest consumption is equal to or higher than 0.7L/100 km.

2 We observe two outliers in those results: the 9<sup>th</sup> vehicle in the short time gap platoon and  
3 the 11<sup>th</sup> in the long time gap platoon. They tend to consume less than the previous vehicle even  
4 if they are at the end of the platoon. This is the consequence of the specific speed profiles of  
5 those two vehicles, showing no overreaction compared to their respective previous vehicles (see  
6 the corresponding vehicles' trajectories in figure 3).

7 The results show that, in the case of five vehicles or less, we cannot identify any difference  
8 in consumption between platoon types. However, as far as their position in the platoon is equal  
9 to or larger than six, then the short time gap ACC vehicles tend to consume more than the HDV.  
10 For the vehicles belonging to the other types, there is no clear correlation between the position in  
11 the platoon and the difference in consumption compared with the HDV. The study of the scatter  
12 plot indicates a potential linear relation between consumption and the position in the platoon. This  
13 linear relation rate differs from one type of platoon to another.

#### 14 *Linear mixed-effect model*

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

$$20 \quad Y = \alpha + \alpha_{long} + \alpha_{mixed} + \alpha_{short} + \beta \cdot position + \beta_{long} \cdot position_{long} + \beta_{mixed} \cdot position_{mixed} \\ + \beta_{short} \cdot position_{short} + \gamma + \varepsilon \quad (2)$$

21  $\alpha_i$  is the intercept for one platoon,  $\beta_i$  is the slope for one platoon,  $\gamma$  captures the impact  
22 of the trajectory-specific error term taken from a normal distribution with mean zero and standard  
23 deviation  $\mu$ ,  $\varepsilon$  captures the impact of the observation-specific error term taken from a normal  
24 distribution with mean zero and standard deviation  $\kappa$ .

25 We perform a likelihood ratio test to understand if the trajectory-specific error term had  
26 a significant effect. Obtained p-value is  $4.5 \times 10^{-24}$ . The result shows that the observations are  
27 significantly correlated across repetitions for the same trajectory (see table 2).

28 The long time gap platoon is used as a reference category. If we compare the HDV results  
29 of the confidence interval of the  $\beta$  values with the mixed platoon and the HDV platoon, we obtain  
30 that they overlap. This shows that the HDV is not significantly different compared to the mixed  
31 platoon or the long time gap platoon regressions. The confidence interval of those two parameters  
32 overlaps. This shows that they are not significantly different.

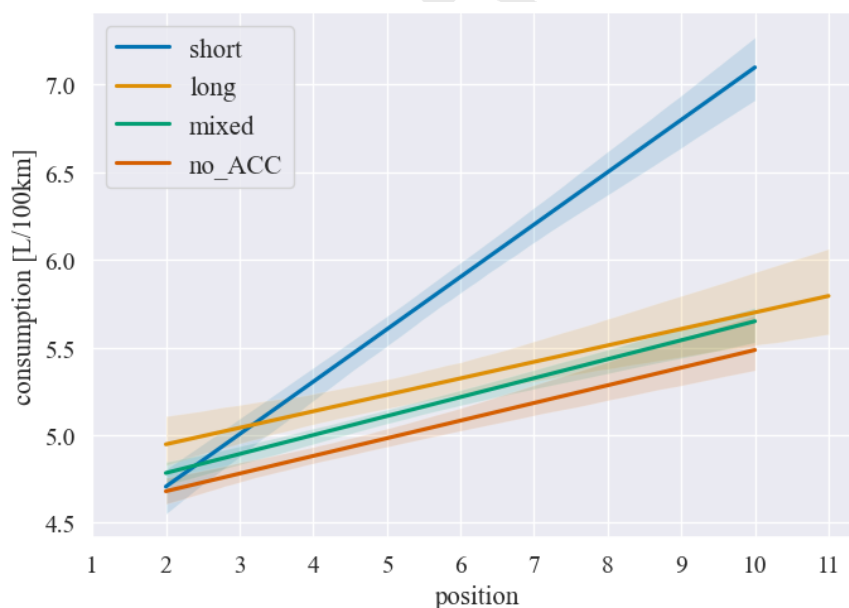
33 On the other side, the confidence interval of the short time gap  $\beta$  does not overlap with any  
34 of the other regressions. This shows that the parameter is significantly different compared to the  
35 three others.

36 Figure 8 presents the four regressions and their confidence interval estimated with the boot-  
37 strap method. It shows that after the fifth vehicle in the platoon, the confidence interval for the short  
38 time gap platoon does not overlap with the confidence intervals of any other platoon type.

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

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 [ $\beta$ ] (reference HDV platoon)	0.101	0.031	3.211	0.001	0.039	0.162
Slope long platoon [ $\beta_{long}$ ]	-0.007	0.040	-0.166	0.869	-0.086	0.073
Slope mixed platoon [ $\beta_{mixed}$ ]	0.008	0.043	0.174	0.862	-0.077	0.092
Slope short platoon [ $\beta_{short}$ ]	0.198	0.042	4.670	0.000	0.115	0.281
Intercept [ $\alpha$ ] (reference HDV platoon)	4.478	0.193	23.192	0.000	4.100	4.857
Intercept long platoon [ $\alpha_{long}$ ]	0.281	0.261	1.079	0.281	-0.230	0.792
Intercept mixed platoon [ $\alpha_{mixed}$ ]	0.089	0.270	0.330	0.741	-0.439	0.617
Intercept short platoon [ $\alpha_{short}$ ]	-0.370	0.269	-1.377	0.169	-0.897	0.157
Group Var [ $\mu$ ]	0.048	0.236				
residuals [ $\kappa$ ]	0.0048					

**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 HDV platoon is used as a reference category for both the intercept and the slope.



**FIGURE 8:** Regressions created out 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 confidence interval was computed using the bootstrap method.

- 1 and the magnitude of string instability (26). Indeed, vehicles in a short time gap setting ACC
- 2 platoons tend to accelerate more due to a larger instability. As a consequence, the amount of fuel

1 needed increases. These findings are based on data collected in a test-track experiment, where  
 2 string instability was triggered by a large deceleration of the leader. To have a global overview  
 3 of the overconsumption of ACC, we need to analyze how often such events might happen in real  
 4 traffic conditions.

## 5 **EVENT OCCURRENCE BASED ON TRAJECTORY DATASET**

### 6 **Selection of the event**

7 The results in the test bench experiment showed that, in the case of platooning, short time gap  
 8 ACC vehicles lead to significant overconsumption when they are the only type of vehicle in the  
 9 platoon. In short time-gap platoon trajectories, two deceleration-acceleration events by the leader  
 10 lead to a string instability as the one described by Wilson (14). The deceleration-acceleration events  
 11 between the first and the ninth follower lead to an 8 m/s minimal speed difference in the first event  
 12 and a 10 m/s speed difference in the second event. Such deceleration-acceleration events are not  
 13 seen in any other trajectory. This leads some authors to suppose that the deceleration-acceleration  
 14 patterns that produce the string instability are also the event producing the overconsumption (13).  
 15 The objective is to identify whether the events that we studied with the engine bench test are  
 16 frequent in real-world traffic.

17 In the OpenACC data, used in the previous part, the leader trajectory was recorded at a 1Hz  
 18 rate and is, due to the sampling rate, noisy. Therefore, we decided to use the first follower speed  
 19 profile for the definition of the event leading to string instability and overconsumption. Looking  
 20 at the speed profiles, we noticed that the string instability is always preceded by a deceleration-  
 21 acceleration with a  $\Delta v > 2.5$  m/s of the first follower. We define this pattern as the triggering  
 22 event that leads to string instability and overconsumption as shown in (13). The triggering event is  
 23 defined when three conditions are met:

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

29 For each first follower trajectory in each ACC platoon within the OpenACC subset that we  
 30 used, we observe two events that correspond to the above definition.

31 Mathematically, we can define the above triggering event as follows. Let  $E$  be a deceleration-  
 32 acceleration event and  $E^*$  be the set of the triggering events that correspond to the description  
 33 underneath<sup>4</sup>:

$$34 \quad E \in E^* \Leftrightarrow \exists t_0, t_1, t_2 \quad (3)$$

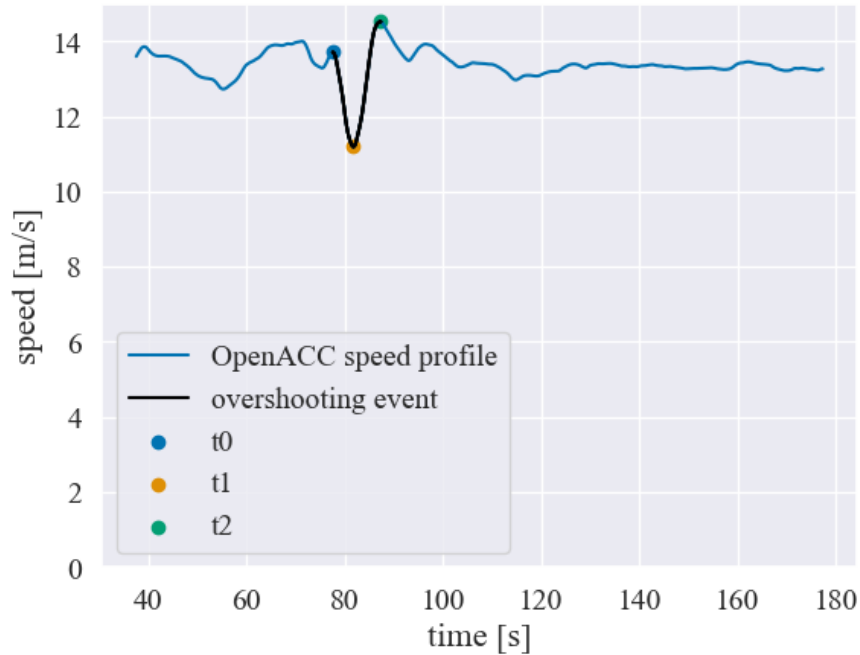
35 where

- 36 •  $t_2 - t_0 < 15s$
- 37 •  $v(t_1) = \min(v(t)) \forall t \in [t_0, t_0 + 100]$
- 38 •  $v(t_2) = \max(v(t)) \forall t \in [t_0, t_0 + 100]$

39 Figure 9 shows an example of such a triggering event and illustrates the mathematical definition.

40 We selected the events that correspond to the above definition in the three ACC platoons'  
 41 first follower trajectories that we used in the engine bench. On average, we have a triggering

<sup>4</sup>numerical values are based on the observation of the data



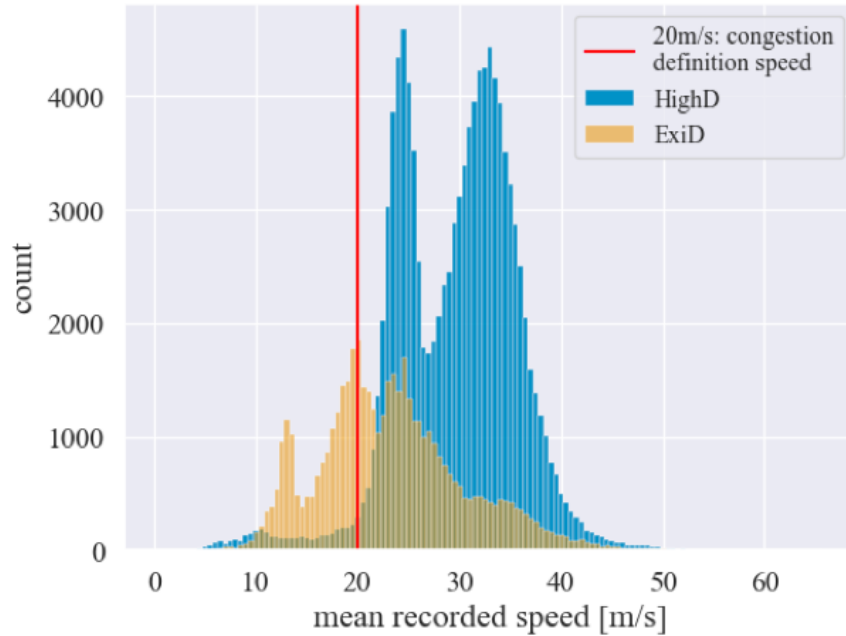
**FIGURE 9:** triggering event

1 event with a deceleration phase that leads to a  $\Delta v_1 = -2.4m/s$  speed difference followed by an  
 2 acceleration phase with a  $\Delta v_2 = 3.5m/s$  speed difference, and a total duration of  $\Delta T = 11.6s$ .

### 3 **Trajectory dataset description**

4 We use the trajectories contained in the HighD (20) and ExiD datasets (21) to determine how often  
 5 the triggering events described in the above section happen in real traffic. These two datasets were  
 6 collected in German Autobahns using drones by a team from Ika and the University of Aachen. The  
 7 trajectories were extracted from the video recordings using a neural network. In total  $9.63 \times 10^8$   
 8 hours of trajectories were collected. The datasets include records of both free-flow and congested  
 9 traffic conditions. The data contain each vehicle's timestep, position, speed, acceleration, current  
 10 lane, time and distance gap, and time to collision. Trajectories were recorded on motorway sections  
 11 near Koln and Dusseldorf. While HighD trajectories were recorded in highway straight sections,  
 12 ExiD trajectories were collected in highway merging and diverging geometries. Figure 10 presents  
 13 the mean speed distribution of each vehicle record of the two datasets.

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



**FIGURE 10:** Speed histogram of the mean recorded speed for each vehicle in HighD and ExiD datasets.

### 1 Event identification result

2 We determined how often such deceleration-acceleration like the ones in the OpenACC triggering  
 3 events happens in congested traffic by analyzing the speed profiles in the selected scenes. For each  
 4 speed profile, we compare on a period of  $[t_0, t_0 + 15 s]$  the dynamic time warping (DTW) distance  
 5 (22) between each triggering event and the speed profile during the period. We then compare the  
 6 mean DTW distance between the HighD speed profile and each of the six *triggering events* (as  
 7 presented in 4.1) to the reference distance, calculated based on the mean distance between the six  
 8 *triggering events* as presented in section 4.1. If the DTW distance is at most five times higher  
 9 than the reference, we consider that the two-speed profiles are comparable during the  $[t_0, t_0 +$   
 10  $15s]$  period. The time window is then moved forward by 2s and we repeated the DTW distance  
 11 computation using the speed profile in the  $[t_0 + 2, t_0 + 17s]$  interval. This method is used to obtain  
 12 the ratio between the temporal periods when a triggering event happens and the total travel time.  
 13 We apply the above method to the 22 records corresponding to the congested situations. We found  
 14 a total of 12,686  $h$  out of  $1.59 \times 10^8 h$  corresponding to triggering events. This means that for each  
 15 1250s we have a 15s interval corresponding to a triggering event.

16 To understand the impacts on global traffic consumption, we compared the findings to  
 17 previous studies. According to a study (27) that used original NGSIM data (28), the mean con-  
 18 sumption in congestion in a motorway with only HDV is 14.7 L/100km<sup>5</sup>. We supposed that the  
 19 mean consumption value corresponds to the consumption of the first follower<sup>6</sup>. We extrapolated  
 20 the consumption of an ACC platoon supposing that from one vehicle in a platoon to another ve-

<sup>5</sup>the values are taken from a 2008 study and might be lower nowadays

<sup>6</sup>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.



1 hicle the ratio  $\frac{Consumption_{veh_i}}{Consumption_{veh_{i-1}}}$  is the same as in our engine bench experimentation results. We  
2 then supposed that each vehicle is part of a 10-vehicle ACC platoon and that each vehicle has a  
3 short time-gap setting, a very pessimistic hypothesis in terms of consumption. Even with such a  
4 pessimistic hypothesis, the percentage of fuel consumption increase is equal to  $1.7 \times 10^{-5}\%$ .

## 5 DISCUSSION AND CONCLUSION

6 In this paper, we studied the impact of ACC vehicles on consumption. To do so, we used a two-  
7 step framework. First, we studied ACC overconsumption in the case of platooning using OpenACC  
8 data (7) in an engine bench. Second, we determined what event could cause such overconsumption  
9 and computed how often such an event happens in real traffic using HighD and ExiD datasets.

10 The results of the engine bench show that ACC vehicles with a short time gap setting  
11 consume more than HDV in the case of platoons with five or more vehicles. The difference in  
12 consumption increases with the length of the platoon. However, the event we identified as the  
13 origin of overconsumption (i.e., an acceleration-deceleration triggering event) is too rare to produce  
14 any noteworthy overconsumption at a global level as it occurs 0.08 % of the time. If the platoon  
15 consumption results are observed in real traffic, the global overconsumption will be only  $1.7 \times 10^{-5}$   
16 %.

17 Notably, the impact of the position in the platoon on consumption is similar between ACC  
18 with long or mixed time gaps platoons and HDV. The mixed platoon is composed of three short  
19 time gap ACC vehicles, followed by two long time gap ACC, followed by three short time gap  
20 ACC. We could have expected, given this composition, that the consumption of the vehicles within  
21 this platoon would have been higher than the ones of the long time gap platoon. Yet it is not the  
22 case. The addition of two long time gap ACC in a platoon mainly composed of short time gap ACC  
23 is sufficient to reduce the consumption to the one of a platoon entirely composed of long time gap  
24 ACC.

25 The findings in this study must be interpreted with caution. We assumed that ACC vehicles  
26 only consume more when platooning and that they consume the same as HDV vehicles in any other  
27 situation. However, there might exist other situations where the ACC leads to overconsumption  
28 that did not analyze due to a lack of data. The engine in the test bench experiment was far less  
29 powerful compared to the engines in the vehicles used to collect the speed profiles in the test track  
30 (11). This means that the engine in the test bench needed to produce more energy to reach the same  
31 torque, leading to an overestimation of the consumption values. However, the comparison across  
32 experimental conditions is expected to be similar with a different engine.

33 The results have important implications for practice and future research. Given that ACC  
34 platoons consume more than HDV only when all ACC vehicles use a short time gap setting, a  
35 specific regulation could be introduced to increase the minimal time gap one can choose in certain  
36 traffic situations.

37 Moreover, the string instability observed in this study is a potential issue for traffic safety.  
38 Such an event, producing harsher and harsher deceleration within the platoon, can trigger in ex-  
39 treme cases a rear-end collision. Some studies that analyzed trajectories right before crashes in  
40 motorways (29) have shown that a deceleration harsher than  $-2.7m/s^2$  in a congested section led  
41 to an increase in the crash probability (1 crash every 88 extreme breaking recording during a 1h  
42 period in the same kilometer). In the OpenACC data, we observed three vehicles that execute such  
43 a deceleration in the short time gap and mixed time gap platoon, and one vehicle in the long time

1 gap platoon. In the case of mainly HDV traffic, we have a 1/1250 probability (by steps of 15s) of  
2 an acceleration-deceleration overshooting. This means that each vehicle in a congested situation  
3 for a period of 15 minutes has a 1/20 probability of overreacting and executing a triggering event.  
4 However, with the increase in ACC penetration rate, this value might increase and result in a higher  
5 crash probability. Future work will focus on assessing the impact of ACC on traffic safety.

## 6 ACKNOWLEDGEMENTS

7 The authors want to thank Biaggio Ciuffo and Kostantinos Mattas from the JRC for the sharing  
8 of leader trajectories within the OpenACC dataset. They also thank them for their explanation  
9 regarding some specific elements of this dataset.

## 10 Author Contribution Statement

11 The authors confirm their contribution to the paper as follows:

- 12 • Study conception and design: Christine Buisson, Silvia Varotto, and Thibault Charlottin;
- 13 • Data selection for the experimentation: Thibault Charlottin, Bruno Jeanneret, Christine  
14 Buisson, and Silvia Varotto;
- 15 • Engine bench test experimentation: Bruno Jeanneret, Thibault Charlottin, and Sylvain  
16 Gillet;
- 17 • Analysis and interpretation of engine bench results: Thibault Charlottin, Bruno Jean-  
18 neret, Christine Buisson, Silvia Varotto;
- 19 • Analysis of event prevalence in real-life traffic data: Thibault Charlottin, Christine Buis-  
20 son, and Silvia Varotto;
- 21 • Data processing and figure creation: Thibault Charlottin;
- 22 • Draft manuscript preparation: Thibault Charlottin, Christine Buisson, and Silvia Varotto.

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

## 24 Code availability

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

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