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

Thibault Charlottin, Silvia Varotto, Bruno Jeanneret, Sylvain Gillet,
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FUEL CONSUMPTION OF ADAPTIVE CRUISE CONTROL PLATOONS: BENCH EXPERIMENTS AND DATA-DRIVEN ESTIMATION FOR REAL TRAFFIC

--Manuscript Draft--

Full Title:	FUEL CONSUMPTION OF ADAPTIVE CRUISE CONTROL PLATOONS: BENCH EXPERIMENTS AND DATA-DRIVEN ESTIMATION FOR REAL TRAFFIC
Abstract:	<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>
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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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6 **Thibault Charlottin¹, Corresponding Author**

7 thibault.charlottin@entpe.fr

8 **Silvia Varotto¹**

9 **Bruno Jeanneret¹**

10 **Sylvain Gillet¹**

11 **Christine Buisson¹**

12

13 *1 LICIT-ECO7, ENTPE, Université Gustave Eiffel, F-69518 Lyon, France*

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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
7 yet. This study examines the impact of ACC systems on traffic consumption using experimental
8 data and traffic records. In this study, we inject the speed profiles of ACC and HDV platoons that
9 follow a similar leader trajectory into an engine bench. Then we identify the event that leads to
10 an overconsumption in the case of platooning. Using HighD and ExiD records, we detect if the
11 events leading to overconsumption often happen in traffic. The results of the engine bench show
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.

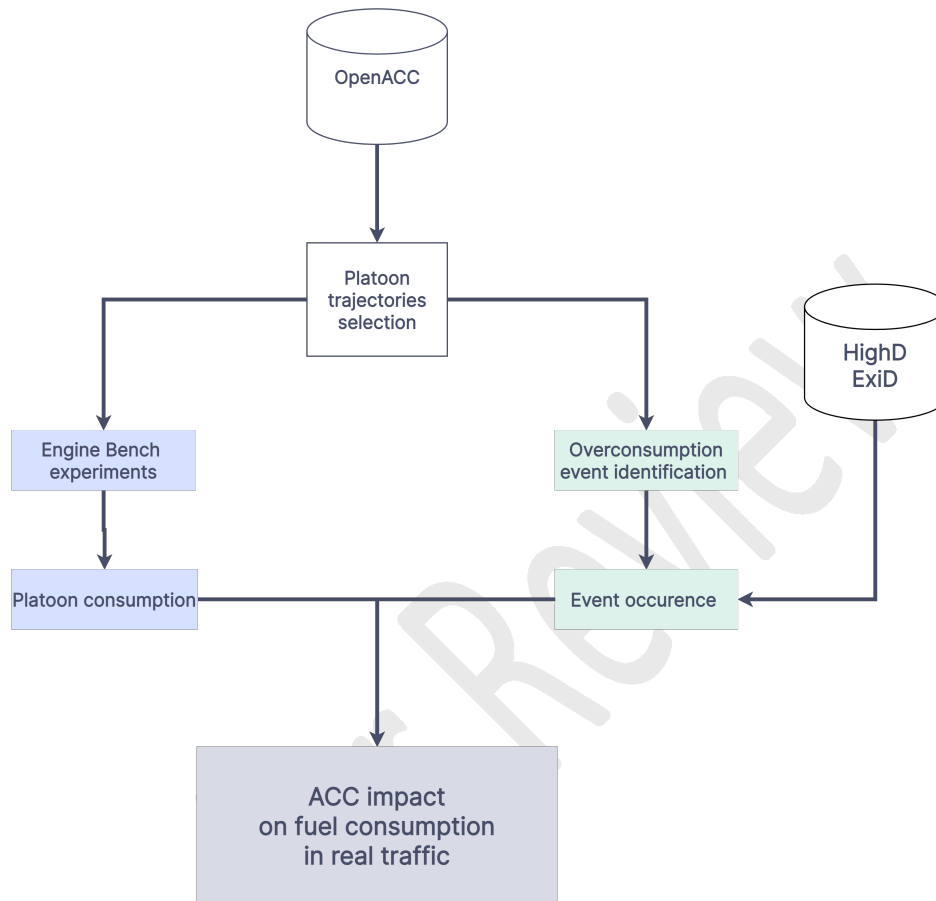


FIGURE 1: Flowchart of the study. Blue indicates the step used to determine the consumption of ACC platoons. Green represents the step to determine if the used trajectories injected in the bench during the part step are frequent or not.

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.

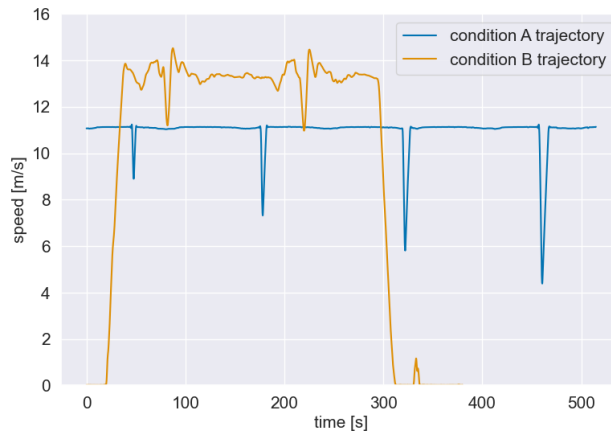


FIGURE 2: The two experimental conditions that exist within the OpenACC dataset

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 group¹ 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

¹e.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.

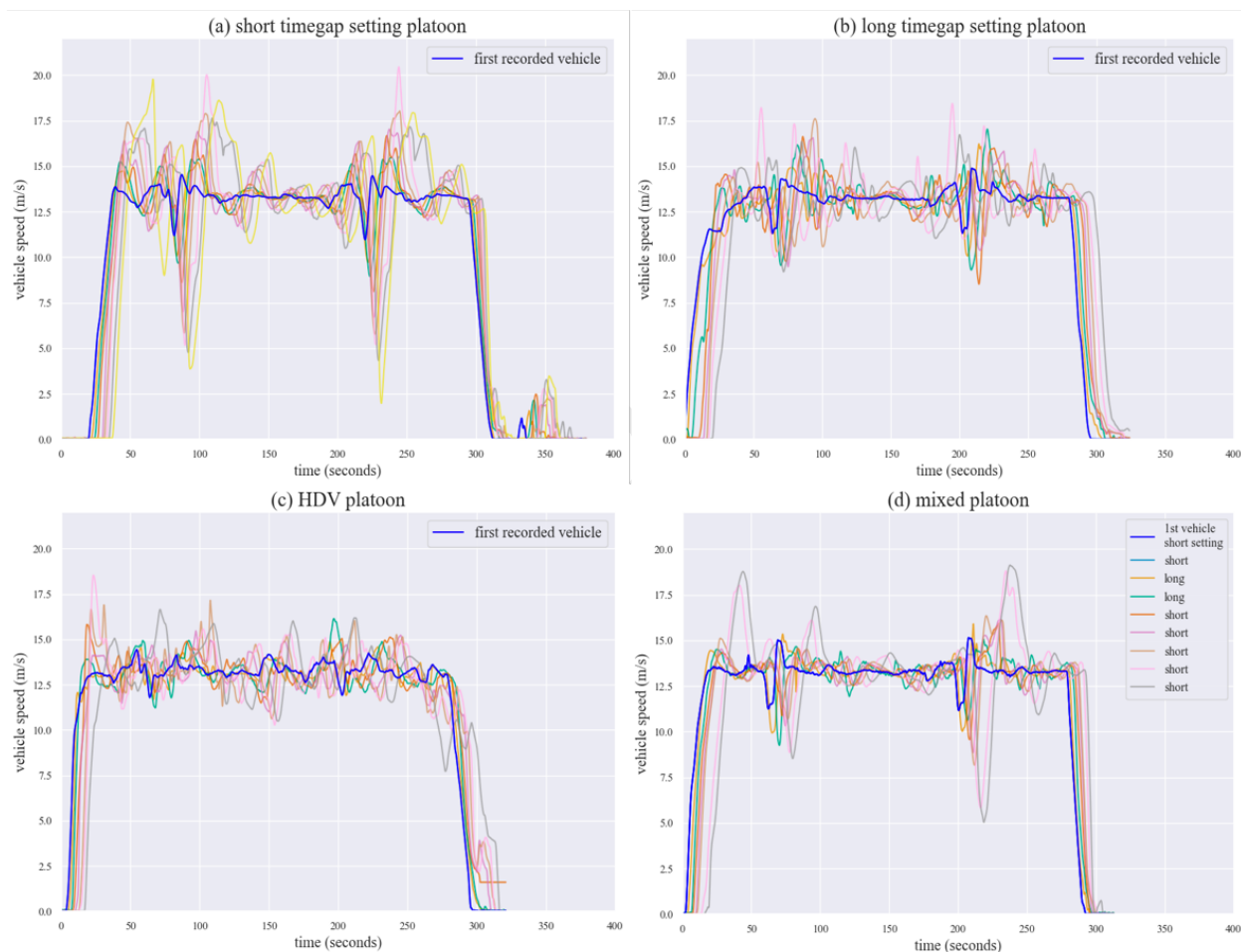


FIGURE 3: Selected platoons for the engine experiment. In the case of the short time gap platoon, events that occur after $t=300s$ are not used.

9 Engine bench experiment

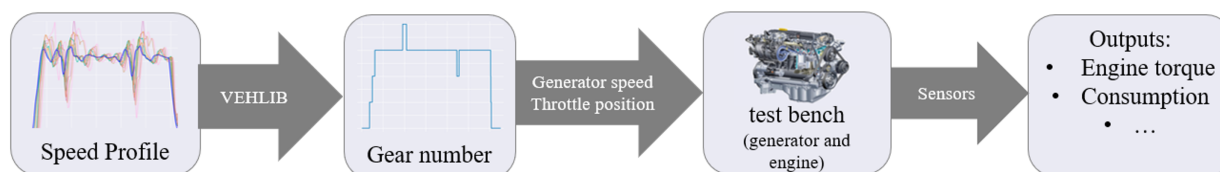
10 The principle of the real-time experiment consists in controlling a real engine in the bench while
 11 simulating the driveline and the resistive force of the vehicle. The engine is from a Renault Kadjar
 12 TCE130, and its characteristics are presented in table 1.

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 minute², 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 rate³. 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

²values of this stabilization speed range from 730 to 780 rotations per minute

³the real-time loop runs at 1kHz

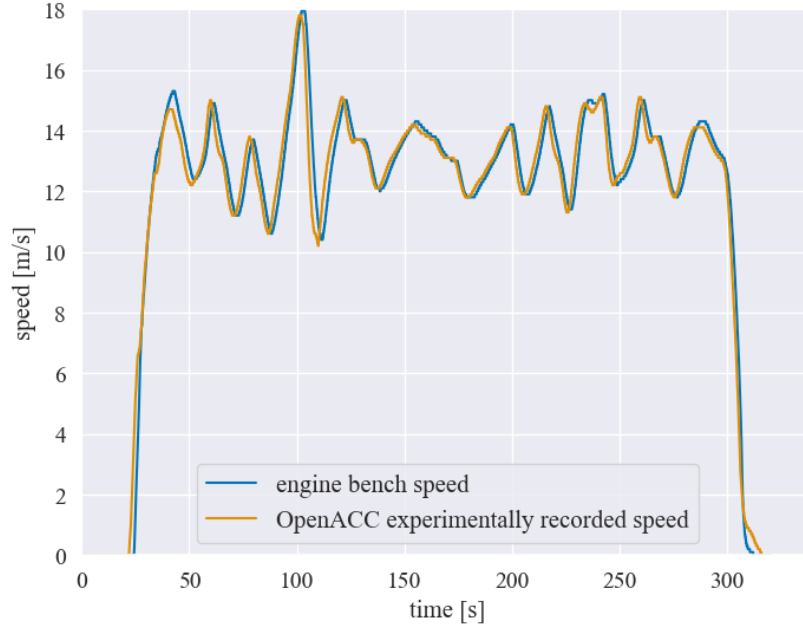


FIGURE 5: Comparison of the engine generated speed and the OpenACC recorded speed. The trajectory corresponds to the 6th vehicle of the long time gap ACC platoon. The results are similar for all reproduced trajectories.

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

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

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.

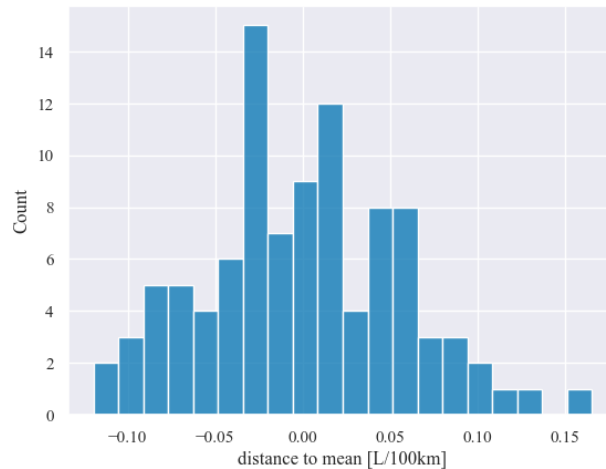


FIGURE 6: Histogram of the distance between the observed consumption of one repetition and the mean consumption of the three repetitions for every trajectory.

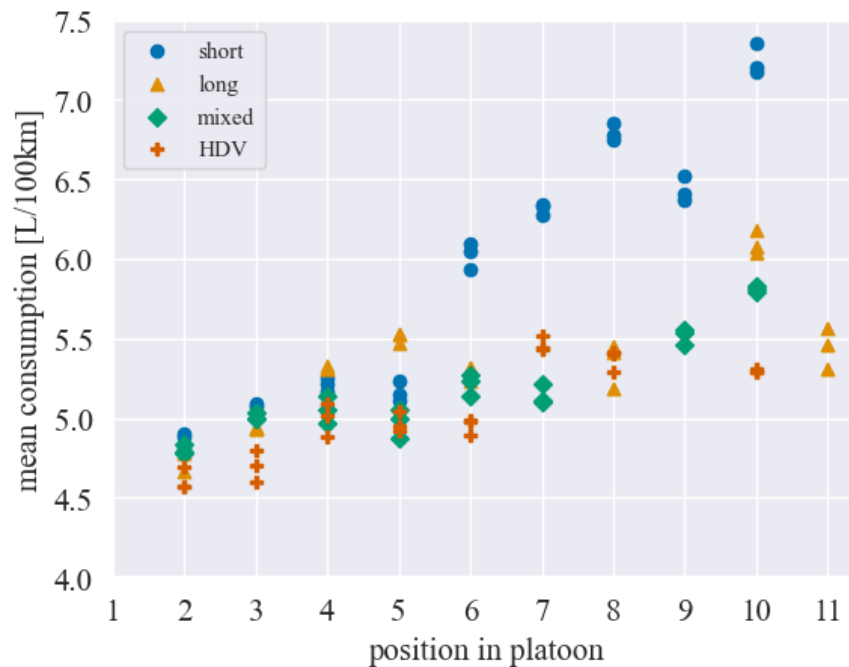


FIGURE 7: Scatter plot of the consumption results. The color indicates the platoon type.

1 Before the 6th 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 2nd to 4th 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 6th 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 9th vehicle in the short time gap platoon and
3 the 11th 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 α_i is the intercept for one platoon, β_i is the slope for one platoon, γ captures the impact
22 of the trajectory-specific error term taken from a normal distribution with mean zero and standard
23 deviation μ , ε captures the impact of the observation-specific error term taken from a normal
24 distribution with mean zero and standard deviation κ .

25 We perform a likelihood ratio test to understand if the trajectory-specific error term had
26 a significant effect. Obtained p-value is 4.5×10^{-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 β 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 β 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 [β] (reference HDV platoon)	0.101	0.031	3.211	0.001	0.039	0.162
Slope long platoon [β_{long}]	-0.007	0.040	-0.166	0.869	-0.086	0.073
Slope mixed platoon [β_{mixed}]	0.008	0.043	0.174	0.862	-0.077	0.092
Slope short platoon [β_{short}]	0.198	0.042	4.670	0.000	0.115	0.281
Intercept [α] (reference HDV platoon)	4.478	0.193	23.192	0.000	4.100	4.857
Intercept long platoon [α_{long}]	0.281	0.261	1.079	0.281	-0.230	0.792
Intercept mixed platoon [α_{mixed}]	0.089	0.270	0.330	0.741	-0.439	0.617
Intercept short platoon [α_{short}]	-0.370	0.269	-1.377	0.169	-0.897	0.157
Group Var [μ]	0.048	0.236				
residuals [κ]	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 IHDV platoon is used as a reference category for both the intercept and the slope.

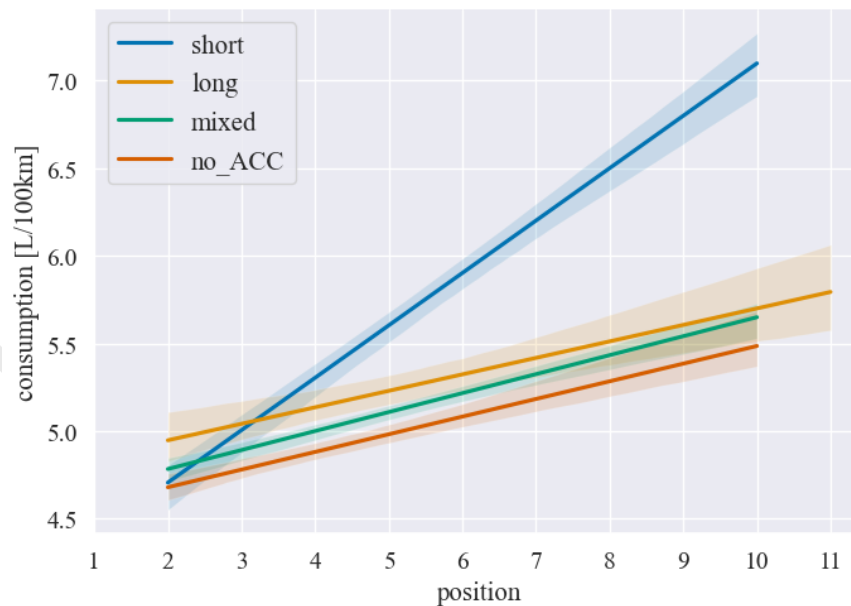


FIGURE 8: Regressions created out of the linear mixed effect model that links the consumption as a function of the position in the platoon for each different platoon type. The confidence interval was computed using the bootstrap method.

- 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 underneath⁴:

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

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

⁴numerical values are based on the observation of the data

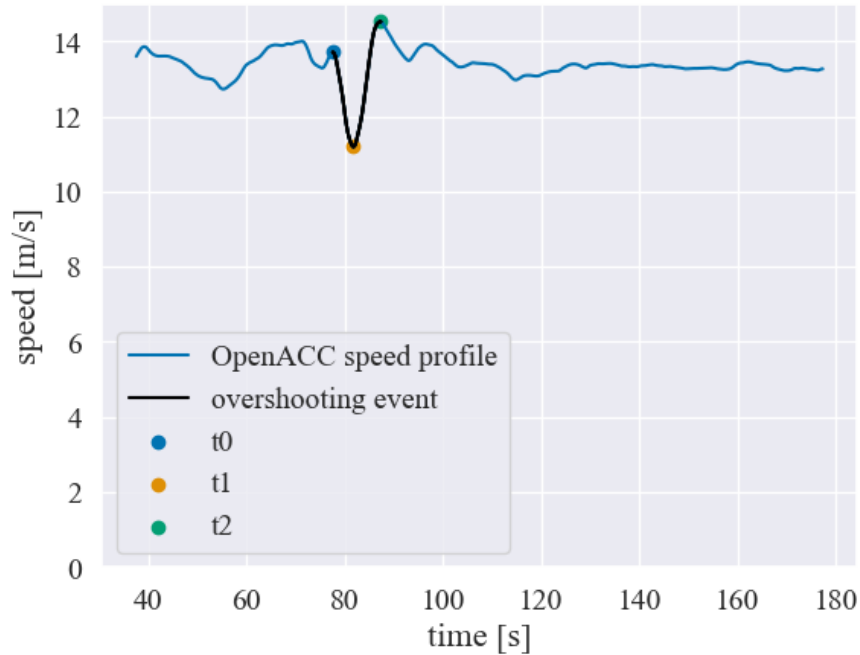


FIGURE 9: triggering event

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 9.63×10^8
 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.

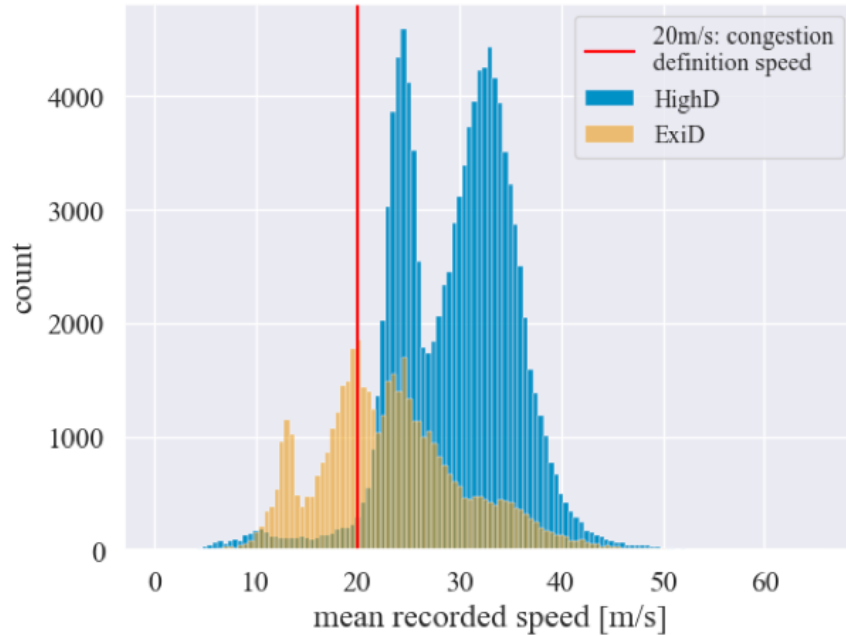


FIGURE 10: Speed histogram of the mean recorded speed for each vehicle in HighD and ExiD datasets.

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/100km⁵. We supposed that the
 19 mean consumption value corresponds to the consumption of the first follower⁶. We extrapolated
 20 the consumption of an ACC platoon supposing that from one vehicle in a platoon to another ve-

⁵the values are taken from a 2008 study and might be lower nowadays

⁶this 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 1.7×10^{-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.

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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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