Response Time and Time Headway of an Adaptive Cruise Control. An Empirical Characterization and Potential Impacts on Road Capacity

Michail Makridis, Konstantinos Mattas, and Biagio Ciuffo

Abstract—Road vehicles are characterized by increasing levels of automation and it is vital to understand the future impact on transport efficiency. Adaptive Cruise Control (ACC) is one of the first and most common automated functionalities available in privately owned vehicles. The effect of ACC on traffic flow has been widely studied by making assumptions on its operating strategy and on some of its important parameters such as the response time and the desired time headway. In the literature, these parameters are usually set to low values, based on the vehicle controller's theoretical ability to respond within a very short time frame. Response time is known to be an important parameter in defining the capacity of the road and therefore, assuming a very short response time, studies usually conclude that systems like the ACC will contribute increasing the road capacity significantly. The present study aims at measuring the actual response time of an ACC-enabled vehicle in car-following conditions. A new methodology for the estimation of the controller's response time and the desired time-gap was developed to this objective. Results show that the response time of the particular ACC controller was in the range 0.8s-1.2s, which is similar to what is commonly assumed for human drivers. In this light, the results of the present study question the common assumption that ACC or other automation technologies necessarily improve traffic flow and increase road capacity.

Index Terms—Adaptive cruise control, response time, time headway, traffic simulation.

I. INTRODUCTION

THE future of driving is expected to be transformed radically, as a result of drastic changes that the introduction of automated and connected vehicles (CAVs) will bring [1]. Driver assistance technologies will evolve up to complete automation (i.e. the ultimate SAE level 5 full automation [2]). From a policy perspective, vehicle automation comes with the promise to significantly increase road safety which is one of the most important challenges in the field. In addition, automation, together with connectivity, is expected to make transport more efficient, to reduce congestion, pollutant emissions and fuel/energy consumption. Considering the expected increase in passenger and freight transport (a growth by about 42% and 60% from 2010 to 2050, respectively) and the fact that the road transport is the main transport mode used in the EU [3],

it is crucial to have technologies supporting the transition to make road transport more sustainable.

Technologies, however, will not transform road transport overnight. During a considerable timeframe, manual, partial and fully autonomous vehicles will coexist on the roads. Vehicle connectivity has still unresolved problems due to limitations of the technology, cybersecurity or standardization issues [4].

Adaptive Cruise Control (ACC), the main topic of this work, is undoubtly the technology on which the transport research community has invested more resources. ACC systems automatically control the longitudinal dynamics of the vehicle and therefore comparing its operations with the car-following models developed by the scientific community becomes very appealing. ACC is regarded as automation in its infancy. The technology is considered already mature enough, yet not massively deployed in the market. Moreover, the industry gives little insights regarding the algorithms behind the controllers. ACC can be enabled and disabled by the driver upon request, and it can automatically accelerate or decelerate a vehicle to maintain a predefined time-gap with a leading vehicle or to reach the desired velocity. ACC uses sensors such as LiDARs, radar or cameras to detect and track the vehicle ahead for measuring the actual distance and speed difference [5]. If a vehicle is travelling in front of the ego vehicle (the ego vehicle is the vehicle equipped with the ACC system) at a slower speed, the acceleration and braking systems are controlled to maintain the inter-vehicle time-gaps level (drivers are not able to set specific values but different time headway levels, from the shortest to the longest), set by the driver [6].

In the present paper, the operational strategy of the ACC system of a commercially available vehicle is analyzed, focusing on two key parameters that affect vehicle interactions and the traffic flow, namely the response time (or reaction time) and the time headway (or time-gap). This type of test campaigns is common in scientific literature. They have been used, for example, to understand the capability of proposed models to reproduce drivers' and vehicles' behavior [7], [8] to measure critical parameters of vehicles' operation strategy [9]–[11] with then the objective to understand the potential impact of new technologies and drivers' style on traffic flow and related externalities [11], [12]).

Several studies have shown the importance of reaction time on traffic flow and road capacity. Drivers do not react to an event instantaneously; rather, they need time to perceive

the event, process the information, decide on a response and finally enact their decision. All these processes introduce a time delay. The smaller the delay, the higher the road capacity and the smoother the traffic flow. Although often neglected, having a realistic quantification of the reaction time within the population of drivers and vehicles is therefore essential in order accurately simulate traffic dynamics [13].

Here, we consider as response or reaction time, the time from the moment that a leader performs an action in the longitudinal direction (either acceleration or deceleration), until the moment that the follower reacts to it (either decelerating or accelerating) under the following conditions:

- The two vehicles are initially under stable car-following conditions with similar speeds.
- The ACC system in the following vehicle is on.

The definition above is similar to the definitions given in the simulation of manual driving, using, for example, the Gipps model [14], where the apparent reaction time parameter is described as the time from the moment that the leader acts to the moment that the follower reacts.

In the literature, there is no clear conclusion regarding indicative values for the response time of the ACC controllers. Some studies focus on the theoretical ability of a controller to have an instant response to an input. In [15]–[18], the authors mention delays in the order of 0.4s to 0.5s in ACC. In some older studies, the ACC response time is considered in the order of 0.1s–0.2s and therefore negligible when compared with the human reaction time of about 1s ([19], [20]). However, in traffic simulation, the overall response time includes not only the controller's physical limits, but also the additional delays due to the communication among the various systems, the calibration of the overall controller and the strategy implemented by the manufacturer. Other studies based on empirical observations like [8] and [9], confirm that delays were observed in the response of the ACC systems but without providing any quantifiable result. Nonetheless, understanding of vehicles' reaction time is very important also for safety reasons. As an example, the authors in [21] highlight the danger of instability in cases of ACC platoons with significant delays in the systems' reaction.

Considering the above, accurate characterizations of the dynamic responses of different ACC systems available in the market are needed to produce realistic predictions of their effects on highway capacity, traffic flow dynamics, safety, emissions and energy consumption, etc. [9].

Parametrization of the time-gap is also important on simulating an ACC-enabled vehicle. On the physical systems, the vehicle manufacturers do not give exact time-gap values, but they let users select from a discrete list of time-gaps levels (i.e. small, medium, large, etc.) from the vehicle ahead. Consequently, for simulation activities, it is important to understand the range of potential time-gap values. In Ntousakis *et al.* [22], it was noticed that the capacity could increase with ACC penetration rate, as long as the time-gap setting is less than 1.10 s - 1.20 s. In cases where this value is higher, the capacity decreases with the penetration rate. Li *et al.* [23] show that smaller time delays and larger time-gaps improve safety performance, but inappropriate parameter

Fig. 1. The path followed by the vehicles inside the JRC-Ispra site.

settings can increase collision risks and cause traffic disturbances. Nowakowski *et al.* [24] presented the following time-gap distributions based on a field test with drivers using manual, ACC and CACC systems:

Manual: 1.64s

ACC: 2.2s (31.1%), 1.6s (18.5%) and 1.1s (50.4%)

CACC: 1.1s (12%), 0.9s (7%), 0.7s (24%) and 0.6s (57%)

Experiments show that the commercial ACC systems are primarily designed for comfort. Vehicle manufacturers seem to add some delay in the reaction to avoid an overreaction feeling that may induce the driver to disengage the system. Adding on top of that the delays due to the interoperability of various vehicle systems, the final response time, that an observer would see, is very close to the human reaction time. The present work, which is based on the preliminary study in [25], proposes a methodology which estimates the operation range of the response time and the time-gap of an ACC controller based on empirical observations. The experiments were conducted on position measurements of two vehicles in car-following formation, over a predefined track (lap test) in the premises of the Joint Research Centre (JRC) in Ispra, Italy, using variable settings in the physical system. Additional tests were performed with the car driven manually. Further analysis is provided regarding instantaneous values along each lap. Ring road simulation results based on calibration on empirical observations are provided as a proxy for the impact of the ACC system on the network's capacity. Results have shown the response times of the ACC under test were found between 0.8s and 1.2s, while the time-gaps, between 1.2s and 2.2.s. Furthermore, under safe driving conditions, the controller has similar response times for both braking and acceleration responses. Finally, results of the calibrated model showed that in the majority of the cases, the network's capacity decreases sharply.

II. EXPERIMENTAL SETUP

The JRC Ispra site is a fully-fenced, 180ha site isolated from the surrounding public road network but with real traffic due to over 2000 employees. The 2.3km-long track is illustrated in Figure 1. The campaign consists of iterative lap tests on the same track using variable parameters (desired speed and headway) for the physical system.

Laps	ACC – Desired speed	ACC – time-gap level	Manual – Desired speed
1 (#17)	40km/h	4	Around 40km/h
3 (#1, #5, #15)	50km/h	4	Around 50km/h
1 (#2)	50km/h	1	Around 50km/h
1 (#13)	50km/h	2	Around 50km/h
2 (#14, #18)	60km/h	1	Around 50km/h
2 (#4, #7)	60km/h	2	Around 50km/h
2 (#3, #6)	60km/h	4	Around 50km/h
5 (#8 - #12)	70km/h	3	Around 50km/h
1 (#16)	70km/h	4	Around 50km/h

For the data acquisition, two vehicles were equipped with two same-type, commercial, GNSS receivers for the acquisition of their trajectory profiles at 10hz. The mean horizontal accuracy reported by the measurement devices was 38cm with a median value of 26cm. The acquired data were post-processed using median filtering for outlier removal and moving average for smoothing. Data processing was performed to avoid the introduction of a time delay to the trajectories.

The ACC system under test is able to keep the preferred speed constant within a range of 30 to 210 km/h and automatically adapt the following distance to the vehicle in front. The vehicle is equipped with Stop&Go functionality, which means that the driver does not have to intervene even at very low speeds. Three radar sensors with a range of up to 150 meters scan the lane ahead, and when the vehicle approaches a vehicle in front, the engine management and brakes adjust the speed, in order to keep the inter-vehicle distance constant according to the desired headway. The driver chooses among four different levels of headway (1-short, 4-long) and the target speed.

Regarding the test specifications, the two vehicles are driven in car-following formation. The vehicle in front, the leading vehicle, is manually driven, with the driver maintaining a desired speed close to the road speed limit, which is 50km/h. The following vehicle has ACC enabled and in the beginning of each lap, the desired speed is communicated from the leader to the follower to ensure car-following consistency for the experiment.

The experimental campaign was designed in a way to understand the operational domain of the controller with regard to the time headway and response time on the average urban speed of 50km/h. Consequently, the vehicle offered 4 different time headway levels and most of the tests were performed on level 1 (shortest) and level 4 (longest). As it is shown in Table I, different target speeds were used from 40km/h to 70km/h. Under car-following conditions the behavior of the controller was not affected by the target speeds. However, on free-flow conditions (when the controller loses the leading vehicle, e.g. in a roundabout), then higher target speeds introduce sharper accelerations, but this is an expected behavior and outside of the scope of this work.

The accuracy of the data acquisition is good enough, having full satellite coverage for the total experiment duration and low location error. In parts of the track, the ACC may become temporarily deactivated (i.e. in roundabouts); however, this part of the track is very short in comparison to the whole track

length (computed below 3%) and the proposed methodology is checked to be robust to this additional noise. The tests refer to a distance traveled of around 52km and a duration of around 90minutes. A summary of the field tests with ACC enabled (18 lap tests) is provided in Table I. Additional five lap tests were performed with the following vehicle manually driven. In those tests, the driver of the following vehicle was instructed to perform normal car-following without any explicit instruction on the desired headway or target speed. More detailed information about the experimental setup can be found in [25].

III. METHODOLOGY

This work proposes a framework that analyzes empirically observed car-following data in order to provide useful insights into the observed response time and time-gap of a commercially available ACC system. First, the prevalent response time and time-gap values are estimated on a lap test basis (Fig. 1). Then the methodology focuses on instantaneous parameter values and their distribution during the experiments. This approach is essential to understand the variation of the time-gap around the target value and whether the controller responds differently during acceleration than deceleration. Finally, a car-following model is used for simulation of the ACC system. For each lap test, the model is calibrated in order to reproduce as close as possible the empirical observations during each lap test. Then, the capacity of a one-lane road is estimated based on the model parameters in order to show the potential impact of the ACC on traffic flow.

A. Estimation of Response Time Per Test Lap

During each test lap the leader maintains a constant speed, and the following ACC-enabled vehicle maintains a constant time-gap according to the desired value set by the driver. The stable state is disturbed when the leading vehicle accelerates or decelerates, which occurs randomly within each lap test. In such cases, the instantaneous time-gap value deviates from the desired one, and consequently, a response from the ACC controller of the following vehicle is initiated in order to counter-balance the deviation. As described in the introduction, assuming that in the initial state two vehicles move with the same speed and zero acceleration, the time between the moment of the leader's action until the time of the controller's response is defined in this work as the response time of the ACC system. However, in empirical observations, there is always injected noise by a variety of factors. Therefore, any proposed method should be robust to a noisy dataset.

In general, a vehicle is expected to have a range of response times depending on several factors e.g. highway or urban environment, critical safety, leader's speed variability, network, weather, road friction etc. In this work, we estimate the response time range under urban conditions with no need for emergency braking. In order to retrieve the operational range of the system, we perform several experiments over the same track.

Cross-correlation is the primary tool used in the proposed methodology, as it has the advantage of the detection of a

signal of known frequency and by definition is developed for determining the time delay between signals received at two spatially separated sensors in the presence of uncorrelated noise [26], [27]. Consequently, this is a suitable tool for the detection of the ACC controller's response time per lap test, since the error in the vehicle positioning as mentioned can be up to 38cm, and this error can grow upon derivation.

Regarding the ACC system, we perform cross-correlation between two time series; the speed difference between the leader and the follower, Δv_{l-f} and the acceleration of the follower. The notion behind this choice of signals is based on the definition of the response time given above: a) on average both vehicles maintain a nearly constant time-gap (i.e. stable state) during a test lap as defined by the user, b) an instantaneous action from the leader (acceleration or deceleration) will trigger a reaction by the follower to counter-balance the effect. Consequently, correlation of the speed difference and the follower's acceleration will reveal the controller's response time.

Given the two stationary signals $\Delta v_{l-f,t}$ and $a_{f,t}$, we apply a time delay T on the acceleration of the follower and we compute the cross-covariance function between these two signals as follows:

$$\sigma_{\Delta v, a_f}(T) = \frac{1}{N-1} \sum_{t=1}^{N} (\Delta v_{l-f,t} - \mu_{\Delta v})(a_{f,t-T} - \mu_a) \tag{1}$$

where $\mu_{\Delta v}$ and μ_a are the means of each time series and N is the number of measurements. The cross-correlation derives from the following normalization:

$$r_{\Delta v, a_f}(T) = \frac{\sigma_{\Delta v, a_f}(T)}{\sqrt{\sigma_{\Delta v, \Delta v}(0)\,\sigma_{a_f, a_f}(0)}} \tag{2}$$

where $\sigma_{\Delta v, \Delta v}(0) = \sigma_{\Delta v}^2$ and $\sigma_{a_f, a_f}(0) = \sigma_{a_f}^2$ are the variances of each signal. The peak frequency corresponds to the estimated delay, i.e. response time for the corresponding test lap. In other words, the response time of the controller is derived by the following:

$$\tau_{delay} = \frac{argmax(r_{\Delta v, a_f}(T))}{T = \{0, 0.1, \ldots, T_{max}\}} \tag{3}$$

where T_{max} is the maximum response time assumed in the analysis. In the present work it was assumed that the response time for both ACC and manually-driven laps cannot be more than 4s.

Per each test lap, we compute one estimated response time for the ACC controller.

The proposed correlation-based method is not the most suitable for the estimation of the reaction time in manually-driven vehicles. Although it can be used for the estimation of the human's reaction time, it is expected that the correlation coefficient value will be lower, because human drivers have higher tolerance on chosen desired time-gap values and desired speeds. Consequently, the delay between a leader's action and a follower's response is not consistent throughout a trip. It can be considered as a rough estimation that it incorporates the driver's tolerance.

B. Instantaneous Response Times and Time-Gap Values

In the previous section, the response time has been estimated per test lap. However, as mentioned, the response time can vary depending on the instantaneous conditions and it can be represented within a range of values for the same lap test. To further investigate on this, we analyze all test laps and identify instantaneous response times of the controller based on the definition and detection of the perturbation events described below. This procedure is important to understand if the response time of the controller is different during acceleration or braking.

1) Detection of Perturbation Events: Similar to the definition in Section A and works in the literature (Treiber *et al.* [28] and Shladover *et al.* [29]), the acceleration of the following vehicle, while on car-following with ACC, is a function of inter-vehicle distance and speed difference:

$$a_f = F(\Delta x, |\Delta v|) \tag{4}$$

where Δx is the inter-vehicle distance, and Δv the speed difference between the follower and the leader. During the designed car-following experiment the leader drives on free-flow without the intention to create perturbations. In this context, per each lap, for the given desired speed, we can assume that the inter-vehicle distance is a value very close to the desired one, as determined by the driver's desired time-gap.

Consequently, we can accept the following relaxation in the definition:

$$\Delta x \approx s \tag{5}$$

where s is the desired inter-vehicle distance for the given desired speed. This condition implies that on average per lap test, the car-following is stable with constant time-gap.

Next, we identify perturbation events inside the same lap test. Such events can be on moments when for some reason the leader decides to either accelerate or decelerate slightly. The initiation of each event is defined by the detection of points of interest, which correspond to moments when both vehicles have the same speed as it is illustrated in Figures 2a and 2b. Each point of interest is considered as the initiation of leader's action. Let this point in time be defined as $t_{i,s}$.

Depending on which vehicle will have greater speed at the following time-step, there are two possible scenarios:

$$\begin{cases} case1 : v_l\left(t_{i,s} + \tau\right) > v_f\left(t_{i,s} + \tau\right) \\ case2 : v_l\left(t_{i,s} + \tau\right) < v_f\left(t_{i,s} + \tau\right) \end{cases} \tag{6}$$

where i is an index of the event, s corresponds to start and τ is the next discrete point in the measurements' timeline. Then, we search for the next time point, that correspondingly fulfills the following:

$$\begin{cases} case\ 1 : v_f\left(t_{i,e}\right) > v_f\left(t_k\right) > v_f\left(t_k + \tau\right), & \forall k\{s, \ldots e\} \\ case\ 2 : v_f\left(t_{i,e}\right) < v_f\left(t_k\right) < v_f\left(t_k + \tau\right), & \forall k\{s, \ldots e\} \end{cases} \tag{7}$$

Let this point in time be defined as $t_{i,e}$, where e corresponds to end.

Consequently, the response time of the controller for this perturbation event is defined as:
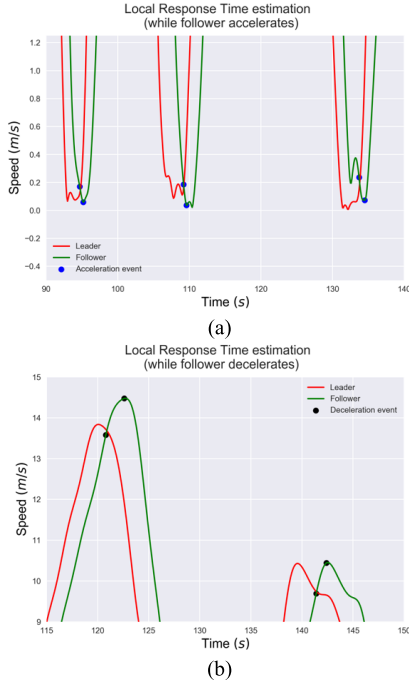
$$r_i \approx t_{i,e} - t_{i,s} \tag{8}$$

Fig. 2. Computation of the response time locally when the follower accelerates (top) or decelerates (bottom).

As it can be observed in Figure 2, the proposed approach provides a correct estimation of the response time when the two vehicles start from steady-state condition and equal speed. In all other cases, the proposed approach produces a slight underestimation of the actual response time. In this light, the resulting response times presented here are sensitive to sensing errors and instantaneous conditions.

2) Response Time During Acceleration and Braking: In the literature, it is not clear whether the ACC controller might have different response values upon acceleration than upon deceleration [30] depending also on occasion, e.g. highway free-flow, congestion, small time headway etc. It is true, that based on the measurements, the response time is not a crisp value that appears across the whole test lap. There is a prevalent frequency, but there is also a distribution of time lags around it.

From each test lap, the perturbation events detected above are categorized as acceleration events (case 1 in Eq. 6) or braking events (case 2 in Eq. 6). For each event, the instantaneous response time is computed according to Eq. 8. Instantaneous response times are noisy due to the nature of the experiment, false-positive perturbation events and the relaxation condition in Eq. 5. Consequently, the discussion here on their distribution rather than some quantitative absolute representation.

3) Estimation of the Prevalent Time-Gap Values Per Lap and Distribution of Instantaneous Values: Usually, ACC systems have a time-gap selection button, in order to give the possibility to the user to select the desired time-gap. The available options are mostly depicted graphically with time-gap levels (i.e. small, medium, large gap) rather than in absolute values (i.e. 1s, 1.5s, 2s). In the literature [31], some ACC controllers have by design values that range between

1s and 2s for the time-gap, which is already in contrast with values found in simulation experiments. In this paper, we define the instantaneous time-gap as follows:

$$h_f(t) = \frac{x_l(t) - x_f(t)}{v_f(t)}$$

$$when \ 1.05 \geq \left| \frac{h_f(t)}{h_f(t - t_c)} \right| \geq 0.95 \tag{9}$$

where h is the headway, t_c is a constant, $x_l(t)$ and $x_f(t)$ the leader's and follower's position at time t respectively. The data that do not fulfil the Eq. 9 are discarded. We indeed need to filter out instantaneous time-gap values whose rate of change is big, because this implies that the vehicles are not in a stable car-following formation.

Per each lap, the desired time-gap is considered the median value of the instantaneous time-gaps:

$$h_{f,lap} = \widetilde{h_f(t)}, \quad \forall t \in lap \tag{10}$$

C. Calibration of the IDM Car-Following Model

The first step before the application of a car-following model in microsimulation is its calibration on real data [32]. In some studies, the calibration process becomes cumbersome, for example, when the quality of the data is poor (noisy or degraded data), or the data volume is low. Regarding the simulation of ACC controllers, most studies rely on parametrization following the values previously reported. In the present paper, we use the collected trajectories to calibrate the parameters of the IDM model. The calibration process is performed in total 18 times, once per lap test with ACC enabled, based on the global least-squared errors calibration on the sums of squared errors (SSE) discussed in the work of Treiber and Kesting [33]. More in details, the following objective function is used:

$$S^{rel}(m_{\hat{\beta}}) = \sum_{i=1}^{n} \left[ln \left(\frac{s_{m_{\hat{\beta}}}(i)}{s_G(i)} \right) \right]^2 \quad \forall m, \hat{\beta} \tag{11}$$

where m is the IDM model with its set of parameters $\hat{\beta}$, i is a distance instance, s_G is the measured spacing for the instance i, $s_{m_{\hat{\beta}}}$ is the simulated speed by the model m with parameter vector $\hat{\beta}$.

IV. RESULTS

Both vehicles drove, in total, 52.8 km. The leading vehicle was driving in manual mode. The length of a single lap is roughly 2.3 km and, in total, the results refer to 23 laps (with the following vehicle driving 18 laps with ACC and five laps in manual mode). The speed limit in the track is 50km/h and therefore the desired speed in the ACC controller was set between 40 km/h and 70 km/h. The whole test was performed under normal weather conditions. The 2.3km lap is not a proving ground but is part of the internal road network of the JRC. However, the authors paid attention not to have the influence of other vehicles during the test execution. Limitations of the experimental setup including the noise always present in the measurements (especially for GPS signal) and the obstacles in the track (roundabout and occasionally other vehicles).
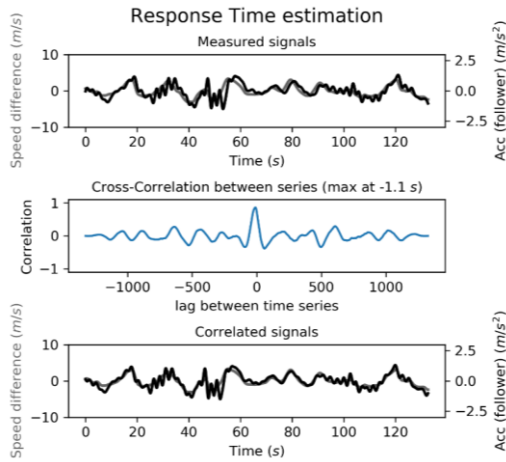
Fig. 3. Estimation of response time based on cross correlation. Top: Uncorrelated time series. Middle: Cross-correlation. Bottom: Correlated time series.

Regarding the GNSS data accuracy, as already mentioned, the average horizontal accuracy reported by the receivers was 38cm with a median value of 26cm. Moreover, the ACC was active during a distance more than 97% of the total distance traveled during the test and it was disengaged a few time for safety reasons by the driver. Regarding data post-processing, it was found that the filtered datasets concluded on the same response times and time-gap values per lap test but with higher correlation coefficient values. However, since the correlation coefficient values reported here are all above 0.8, no data filtering on the trajectories was applied in this work.

For each lap test, the methodology performs cross-correlation between two time series, the acceleration of the follower and the relative speed difference of the two vehicles. An illustration of the procedure on an example lap test is provided in Figure 3. The upper figure shows the vehicles' speed difference (action – gray – left axis) with the acceleration of the follower (response – black right axis). An apparent lag can be observed between two time series. The central figure depicts the cross-correlation result with a distinctive peak on -1.1 seconds. The bottom part of the figure is obtained after shifting the two series in order to show the position that maximizes their correlation and consequently corresponds to the estimated response time.

A. Driving With ACC

In the specifications of an ACC controller, it is noted that the module responsible for the following behavior is based on characteristic lookup tables that ensure human-like behavior depending on the object's distance and relative velocity [31]. The theoretical response delays of the controller can be minimal. However, as already observed, the actual response time can be significantly bigger. Additionally, sharp acceleration or deceleration rates can lead to discomfort for the passenger. The results in this section confirm that the ACC controller is designed with an evident priority to mimic human driving conditions in terms of comfort, while on the same time to ensure safety by keeping long-enough headways. It is true that the design of such controllers may change in the
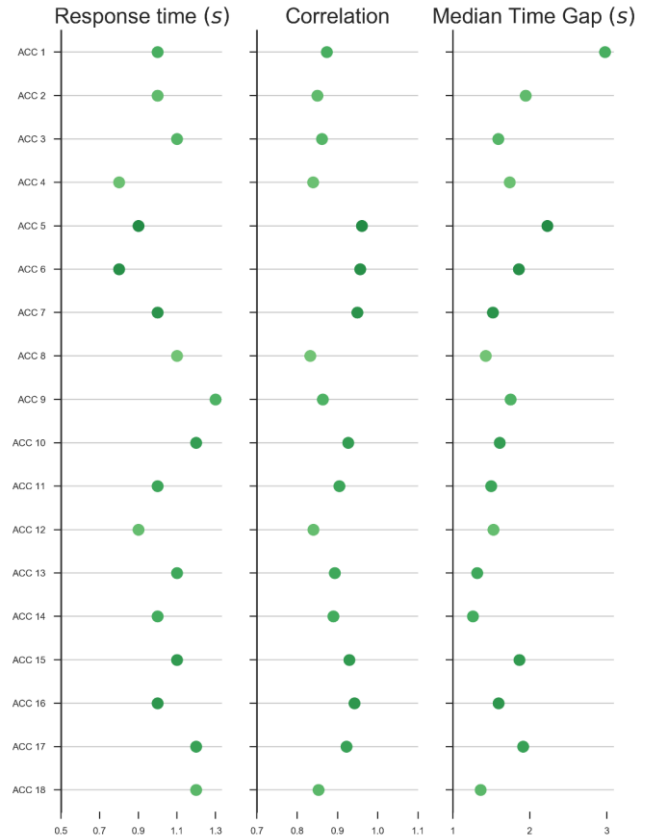

Fig. 4. Results with estimated response time, correlation strength and indicative time-gaps for each lap test.

future, however, mass deployment of such systems in present networks would probably have a negative impact on the traffic flow and network capacity.

In the literature, the response time of a human driver is estimated between 1s and 1.8s [34]. Desired time-gaps of human drivers are thought to be in the range of 0.5–1.5s generally [35], [36]), while the time-gaps for ACC systems vary between 1s and 3s, with the main focus on desired time-gaps of 1.2–1.8s [36], [37]).

The obtained response times per lap test are reported in Figure 4. The number of each lap, i.e. ACC 1 – ACC 18 corresponds to the order that each lap was processed. These numbers are the same with those reported in Table I. Consequently, the reader can use the number of the lap and find the target speed and the headway setting from the table. In the figure there are three columns, the first one provides the estimated response time, τ_{delay}, the second one shows the maximum value in the correlation function $max(r_{\Delta v, a_f}(T))$ and the third one corresponds to the median operational time-gap value for the corresponding lap as an approximation for the specific test, h_{lap}. The bullets in the figure are colored based on the value of $max(r_{\Delta v, a_f}(T))$ per lap test, that is, the darker ones indicate strong correlation (tall peaks with values close to one) while the lighter ones point to weaker correlation (shorter peaks with lower values).

It is interesting to notice that the range of the obtained values is narrow. The lower correlation coefficient values has been found above 0.8, which indicates consistency and robustness.
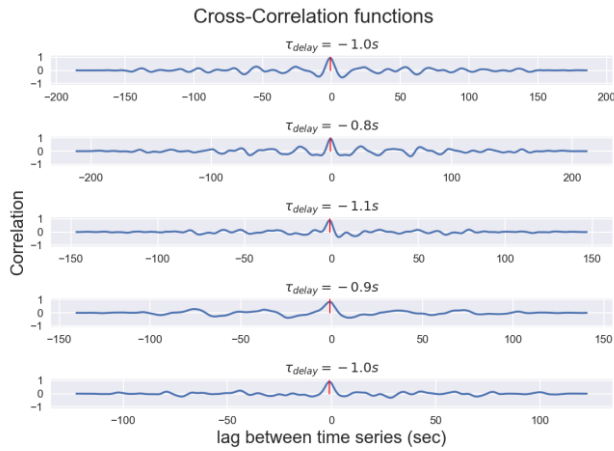
Fig. 5. The correlation functions for five indicative lap tests. The main frequency corresponds to the response time, taking values around 1 second in each case.

The estimated values for the ACC response time per lap test are between 0.8s and 1.2s, while the median operating time-gaps, as an approximation of the desired headways, have been found between 1.2s and 2.2.s. Consequently, the estimated response time of the controller is close to the values reported in the literature for human drivers. Additionally, the time-gap of the ACC system can be even larger than the desired time-gap of human drivers.

Two lap tests were discarded because the computed correlation coefficient value was very low. Also, it can be observed that for the first lap test in Fig. 4 the estimated time headway was found just below 3s, which is a relatively high value in comparison to the rest. Upon further investigation, it was found that this test lap included high-frequency oscillations of the speed difference between the two vehicles, which means that for most of the path the vehicles were not driving in equilibrium. Time headway estimation is more robust under stable car-following conditions.

Finally, Figure 5 illustrates the correlation functions for five lap tests. The peak frequency is obvious in each of the five cases despite the different variability of the oscillations around it. These results showcase that the performance of cross-correlation is consistent and the proposed methodology provides robust results.

B. Manual Driving

During the measurements, some laps were performed with the ACC system turned off, i.e. manual driving. As mentioned in Section III A., the proposed correlation-based method becomes less precise for estimation of the reaction time in manually-driven vehicles, in terms of lower correlation coefficient values. Consequently, the delay between a leader's action and a follower's response, presented in this section for lap tests when the following vehicle was manually driven can be considered reliable only as a rough estimation of the human response time.

Based on the above, the results referring to manual driving (Table II) are presented in this study only as a

TABLE II
RESULTED REACTION TIME WITH THE SAME METHODOLOGY FOR A HUMAN DRIVER

RESPONSE TIME	CORRELATION	MEDIAN TIME-GAP
1.4	0.78	1.21
1.0	0.73	1.22
1.4	0.78	1.43
1.3	0.78	0.73
2.1	0.57	0.63

complementary analysis. As expected, the corresponding correlation of the time series for the manually driven laps is significantly lower than the one observed in ACC mode. The reaction time of a human driver is, as anticipated, longer than the one from the ACC controller. The resulted response time values are scattered within a range from 1.0s to 2.1s. This significant difference can be explained if one considers that a) the tests were conducted under safe conditions, for which the human driver is more tolerant to variability in the speed of the leader and b) the human driver does not react on the basis of the time-gap variation, rather on the intuitive interpretation of the distance from the leader (comfortable/safe or uncomfortable/unsafe). Results in the literature fall within the same range [24]. Accordingly, the median time-gap values found per lap test are smaller than those observed for ACC. Here, we can comment again that due to the safe nature of the experiment and the relatively low speeds in a non-congested network, it is normal that human drivers will feel comfortable to stay close to the leading vehicle. Also, in low speeds, the variation of the operational time-gap should be higher, leading to high variations of the desired time-gap as shown in Table II. Again, the resulted values are in line with the literature where the desired time-gaps of human drivers are thought to be in the range of 0.5–1.5 seconds generally [35], [36].

It is worth noting that the five-lap tests with human driver were performed by the same person, which was instructed to follow the leader typically without any explicit definition for the headway, distance, desired speed or reaction time. Although one would expect a homogenous behavior for the driver, the results reveal a variation in the response time and the time headway. It can be inferred that either these metrics are not suitable for the description of different driving styles, or the driver does not employ a deterministic strategy (tolerance), and his behavior varies. In future work, it would be interesting to try to quantify the above-mentioned variation and perform a comparison of different drivers on the same vehicle.

C. Response Time and Time-Gap Distributions for the ACC System

The longitudinal control function of the ACC controller is dictated by several factors such as situation specific controls (set speed, follow controller, curve speed), the capabilities of the vehicle (power curve, gear shifting), and a set of safety/comfort thresholds that limit acceleration and deceleration to acceptable levels. Moreover, it would be interesting to see if the ACC has different response behavior while
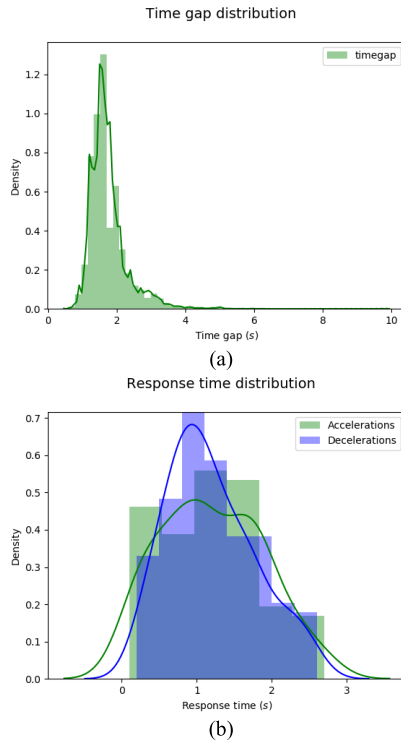
Fig. 6. Top: Distribution of the instantaneous operational time-gap of the ACC system. Bottom: Distribution of the local response times upon acceleration and deceleration of the ACC system.

TABLE III
PARAMETERS OF IDM CALIBRATED ON THE ACC TEST LAPS

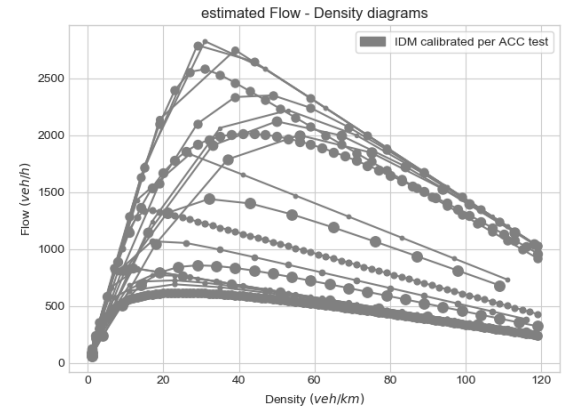| PARAMETER	MIN	MAX
MAXIMUM ACCELERATION a_{max}	0.1M/S2	MAXIMUM ACCELERATION IN THE SPEED PROFILE
DESIRED SPEED V_d	40KM/H	70KM/H
MAXIMUM DECELERATION b_n	MINIMUM DECELERATION IN THE SPEED PROFILE	-0.1
DELTA	0.1	10
MINIMUM DISTANCE AT STOP, ds	2	4
TIME HEADWAY, th	1	4

Fig. 7. Flow over density diagrams for all 18 lap tests with IDM parameters calibrated on the ACC behavior.

accelerates than while decelerates. To the authors' knowledge, there is not any similar study in the literature. In order to compare these response times, perturbation events are detected according to the methodology described in Section III and they are categorized to acceleration or braking events.

In the total of 18 lap tests, there were detected 95 acceleration events, 137 deceleration events and 37826 instantaneous time-gaps.

The time-gap oscillates around the desired value set by the user and indeed, Figure 6a shows that the time-gap distribution has a high peak slightly above 1.5s and a second, smaller one, near 2s. In these results, the threshold constant t_c is set to 3s. The peak values are also the official time-gap limits in similar ACC controllers on the market [31].

The response time distribution shows that the ACC controller behaves in a similar way when accelerating and when decelerating. Results are illustrated in Figure 6b. The range of values is obviously wider than the response time per lap but the interquartile values confirm the ranges derived with the other approach. It is worth noticing that, there are also very low instantaneous values of response time detected, confirming that this method provides a possible underestimation of the response time when the event does not start with the two vehicles in steady-state conditions. Concerning the difference of response time in acceleration and braking events, although the distributions are quite similar, a skew is observable in the braking distribution, with response time slightly lower. Although not self-evident, it makes sense that when the vehicle has to decelerate, the response of the controller should be crisper. It should be mentioned, though, that during the

measurement tests, the car-following behavior was normal without sharp accelerations or decelerations. Consequently, the response behavior of the ACC system on more critical situations such as emergency braking is still under question.

D. Impact of ACC on the Capacity of a Ring-Road Toy Network

Results in this work give a better overview on the observable response time and time-gap values of a commercially available ACC controller. Such empirical estimations are particularly useful in traffic simulation studies in order to better reproduce the dynamics of the vehicle in the longitudinal direction. In this section, we show the effect of the different response times collected with the experiment on road capacity.

Since in most studies, the Intelligent Driver Model is used to simulate the ACC behavior, this model has been calibrated on the data from each lap test, considering that each test is an independent ACC driver (variable conditions). The calibration is carried out as described in Section III and using the ranges defined in the Table III.

Then, the model is used in a simple one-lane ring-road simulator to characterize the resulting density-flow diagram as showed in Figure 7.

Different parameters sets produce very different density-flow diagrams and therefore, very different road capacity levels. In particular, in the majority of the cases, the resulted capacity is very low. The parameters that play the most crucial role are the time-gap and the delta parameter of the

IDM model. The first indicates how important is the realistic parametrization of headway in simulation studies. The second alters the curvature in the acceleration over speed representation of the IDM model. Low delta values can lead to slow acceleration profiles, while high values to more aggressive ones. From the results, it can be observed that the impact of controllers such as the one under test can be dramatic in real networks and highly dependent on the ontological stochasticity of a driving profile even for ACC-enabled vehicles. In this light, the assumption that ACC-enabled vehicles may already contribute improving traffic flow is at least questionable.

V. Conclusion

The proposed framework analyzes empirically observed car-following data in order to provide useful insights into the observed response time and time-gap of a commercially available ACC system. The experiments were conducted with two vehicles in car-following formation in the JRC in Ispra, Italy. The campaign consists of 18 lap tests on the same track using variable parameters (desired speed and headway) for the physical system and 5 lap-tests with the vehicles driven manually.

The proposed methodology uses three different approaches. A first approach uses a cross-correlation and provides estimates of the system's response time and time headway on a track scale. The second approach focuses on instantaneous events in order to provide instantaneous estimations of the above parameters and understand variations in the behavior of the controller under acceleration and deceleration conditions. Finally, the third approach incorporates the parameters' estimates within a car-following model in a microsimulation framework. The model is calibrated and used as a proxy to introduce multiple ACC instances, showing the potential impact of ACC systems on traffic flow.

The estimated values for the ACC response time per lap test are between 0.8s and 1.2s with a correlation value over 0.8, close to reaction time values of human drivers reported in the literature. The median operating time-gaps, as an approximation of the desired headways, have been found between 1.2s and 2.2.s, slightly higher than the time-gap values of human drivers reported in the literature.

Moreover, the distribution of the operational response times (instantaneous) shows that the ACC controller operates similarly during acceleration and deceleration events, with the latter distribution being slightly skewed towards slightly lower response time.

Finally, the IDM parameters were calibrated and the model was used as a proxy for showing the potential impact of the ACC under test within a network. Results show that different calibrated parameter sets can result in different maximum capacities for the ring-road. In the majority of the cases, the resulted capacity is low, questioning the widely accepted hypothesis that ACC enabled vehicles are beneficial to traffic flow. The parameters of currently available controllers in the market are unknown and probably similar but not identical. Consequently, the aim of this work is to give valuable insights in a topic that is only marginally discussed in the literature,

but at the same time it is not aimed at generalizing the present outputs to most or all controllers. Future research will include different vehicles and different brands in order to be in the position to draw better inference on the possible impact of ACC and other automated functionalities on traffic flow and road capacity.

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