Proportional Integral Derivative Decentralized Control vs Linear Quadratic Tracking Regulator in Vehicle Overtaking within a Platoon

Alessandro Bozzi[a], Roberto Sacile[b] and Enrico Zero[c]
DIBRIS – Department on Informatics, Bioengineering, Robotics and Systems Engineering, University of Genova, Genova, Italy

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Abstract: This paper introduces a comparison between a decentralized Proportional Integral Derivative (PID) controller and a centralized Linear Quadratic Tracking (LQT) controller to automatise the exchange of two inner vehicles inside a platoon moving on a straight path. Lomonossoff's model is used to represent vehicle's longitudinal dynamics. A case study is presented to demonstrate the effectiveness of both controllers respectively on nonlinear and linearized model.

1 INTRODUCTION

Autonomous vehicle (AV) is an important research field of the current century which consists in a car acquiring data and information in real time about the neighboring environment and driving without the human interaction for a specified period of time. AVs are classified accordingly with the vehicle autonomy degree in six levels, from level 0 where there is no driving automation to level 5 where there is a full driving automation (SAE, 2014). Equipping cars and light vehicles with this technology will likely reduce crashes, energy consumption, pollution and congestions (Anderson et al., 2014). One of the main causes in road traffic accidents is the human behavior. An application of new technologies to monitor driver's condition becomes essential to detect anomalous driver behavior and prevent near miss accidents has been performed (Zero et al., 2019).

As autonomous vehicles supplant human drivers, automation's ability to communicate and cooperate with people will become more important. Not all vehicles are equipped with sensors for autonomous driving, so it is also important that the autonomous vehicles interact with the human drivers of other vehicles. A cooperative maneuver among one autonomous car and two human-driven vehicles equipped with sensors and actuators has been tested in (Alonso et al., 2011). In order to perform this work, the system needs the position, speed, and intentions of the cars involved in the maneuver. The authors managed the speed of human-driven vehicles to make each element arrive at the intersection at the same time, in order to analyze the behavior of the unmanned car.

In any urban environment, the vehicle will need to react safely to each type of unexpected event such as ill-behaved pedestrians, and pranksters (Koopman and Wagner, 2017).

In several works, the aim is the management of vehicle trajectory while driving, in particular the minimization of the gap between the planned and the real trajectory. A novel dynamics controller that consists of longitudinal and lateral controllers for autonomous vehicle to simultaneously control it as closer as possible to the driving limits while following the desired path has been proposed (Ni and Hu, 2017).

Recent works are not focused on the behavior management of just one vehicle but they focus on the behavior of more AVs, namely a platoon of vehicles. This aspect requires more than one sensor embedded in the vehicle. The management of trajectory of an AVs platoon is fundamental because it is related to another goal - the reduction of energy consumption. Indeed, it is verified that AV technologies reduce fuel consumption by managing better acceleration and deceleration than a human driver (Anderson et al., 2014).

The management of a trajectory for a vehicle in a platoon is more complex rather than on a single AV due to the unexpected events during the transit which

[a] https://orcid.org/0000-0002-2436-0946
[b] https://orcid.org/0000-0003-4086-8747
[c] https://orcid.org/0000-0002-9995-1724

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can affect differently each element of the platoon. Indeed, vehicle approaching or detachment from neighbors can frequently happen. To generate countermeasures for each element of the system, in order to restore the correct position, speed and interdistance and guarantee passengers' safety, a control system based on a real-time robust trajectory has been tested (Bozzi et al., 2021). In order to ensure the safety of maneuvers to let an external vehicle be inserted into the platoon or alternatively to let a vehicle of the platoon leave it, a longitudinal Model Predictive Control has been implemented (Graffione et al., 2020a). The automation of the overtaking maneuver such as the entrance and exit from a platoon is considered to be one of the hardest challenges in the development of autonomous vehicles. In this direction a fuzzy controller has been performed to reduce the human interaction during this maneuver (Naranjo et al., 2008).

This paper proposes a comparison between the performance of a PID controller on a nonlinear continuous model and of a Linear Quadratic Tracking (LQT) controller on a linearized discrete model to swap the central vehicles of a four-vehicle platoon moving on a straight path. The former control system is decentralized as each vehicle has its own PID to handle the maneuver, similarly to (Stankovic et al., 2000), while the latter is computed in a centralized way, as usually in these cases the leader governs the vehicle position giving the optimal speed and acceleration to the followers (Graffione et al., 2020b).

The remainder of this work is organized as follows: Section II reviews the nonlinear and linear model tested and it shows the driving scenario. In Section III the case study is analyzed and the results related to the nonlinear and linear controller simulation. In Section IV conclusions about the comparison of the two models are reported and the further developments of this work are proposed.

2 MODELS AND METHODS

In the literature, the longitudinal models are largely investigated. This happens because the vehicle's displacement can be often subdivided in longitudinal and lateral motion and the two are assumed additive. This paper tackles the problem in the same way but using a different longitudinal representation for elements of the platoon. Indeed, they have been modeled through the Lomonossoff's equations, mainly used for trains (as in (Lu et al., 2011)) but easily adaptable for cars modelization. It faithfully represents vehicle's evolution overtime and provide the possibility of taking into accounr vehicle's parameters such as mass and frictions, that have primary importance especially when dealing with trucks.

Table 1: Davis constants.

C^a	9
C^b	0.06
C^c	0.023
W	2

The model chosen is nonlinear due to a quadratic term function of the speed.

2.1 Nonlinear Model

The Lomonossoff's equations are:

$$\begin{cases} \dot{x}(t) = v(t) \\ W'\dot{v}(t) = f(t) - (C^a + C^b v(t) + C^c v^2(t)) \\ \qquad\qquad -Wg\sin\alpha(t) \end{cases} \tag{1}$$

where:

- $x[m]$ and $v[m/s]$ are state variables, respectively position and speed of the vehicle
- $f[kN]$ is the control input, corresponding to the tractive effort
- $C^a[kN]$, $C^b[\frac{kN}{m/s}]$, $C^c[\frac{kN}{m^2/s^2}]$ are the Davis constants, related respectively to mechanical resistance, viscous mechanical resistance and aerodynamic resistance
- $W[tonnes]$ is the vehicle's tare mass
- $W'[tonnes]$ is the vehicle's effective mass, including rotary allowance
- α is the slope angle of the position of the vehicle

They represent the dynamics of the longitudinal motion for the individual vehicle by prompting a tractive effort, with a maximum value similarly to what happens in train modelization.

In the following, it is assumed that $\alpha = 0$, i.e. vehicles are traveling on a flat road. Vehicles are considered homogeneous and their parameter estimation for the case study, which deals with heavy-duty vehicles (HDVs), is listed on Table 1. The choice of analyzing HDVs is due to recent literature results, which reveal that the improvement in their performance is significant if they are placed in ascending order based on their braking capabilities (Alam et al., 2014). So, an algorithm to swap inner vehicles of the platoon can provide long-term efficiency in fuel consumption and CO_2 emissions.

2.2 Linear Model

The model presented in (1) can be linearized for each planned instant t_p around a working state/control couple $(\bar{v}, \bar{f})$, supposing no acceleration in that instant of time.

The resulting linear approximation that represents the evolution of the system overtime is:

$$\delta\dot{x} = A_p \delta x + B_p \delta f \tag{2}$$

where:

$$\delta x = [x(t) - \bar{x}(t) \quad v(t) - \bar{v}(t)]^T, \quad \delta f = [f(t) - \bar{f}(t)] \tag{3}$$

$$A_p = \begin{bmatrix} 0 & 1 \\ 0 & -\frac{C^b + 2C^c \bar{v}(t)}{W'} \end{bmatrix}, \quad B_p = \begin{bmatrix} 0 \\ 1/W' \end{bmatrix} \tag{4}$$

It has to be noted that the A_p matrix is time-variant, as it depends on the actual speed of the vehicle. In other words, the matrix A_p is computed at each sampling instant in order to let the system work around an operating point that varies overtime and follows the trend of vehicle's speed.

The control algorithm is applied to the discretized system with a sample time, for the case study, of $100ms$.

2.3 Driving Scenario

This paper analyzes a driving routine in which two inner vehicles exchange their position while the platoon is moving on a straight path. Initial positions of platoon is represented in Fig. 1a.

This kind of maneuver can be seen as an overtaking with space constraints, since the vehicle behind has to:

- position itself on the fast lane, thus exiting from the string formation (Fig. 1b)
- overcome the vehicle in front of it in the platoon formation (that in the meanwhile has to favor the overtaking with a slow deceleration)
- settle at the correct distance between its neighboring vehicles (Fig. 1c)
- come back to the platoon lane (Fig. 1d)

The maneuver, graphically represented in Fig. 1 has to be performed keeping similar speed with respect to the rest of platoon and in a reasonable time frame. Moreover, for the whole time, vehicles involved in the swap have to prevent getting too closer to their neighbors, thus endangering passengers' safety.

The role of each element can be summarize as follows:

- Vehicle #1 has to proceed at constant speed and measure the distance to its follower, in order to improve the reconstruction of the surroundings
- Vehicle #2 decelerates in order to favor the overtaking of vehicle #3, while measuring the distance from the leader and the last element of the platoon
- Vehicle #3 overtakes vehicle #2 and measure the distance from it and from the leader, in order to re-enter the string formation in the best position possible
- Vehicle #4, similarly to vehicle #1, has to proceed at constant speed and increase the knowledge of the environment by providing its measurements

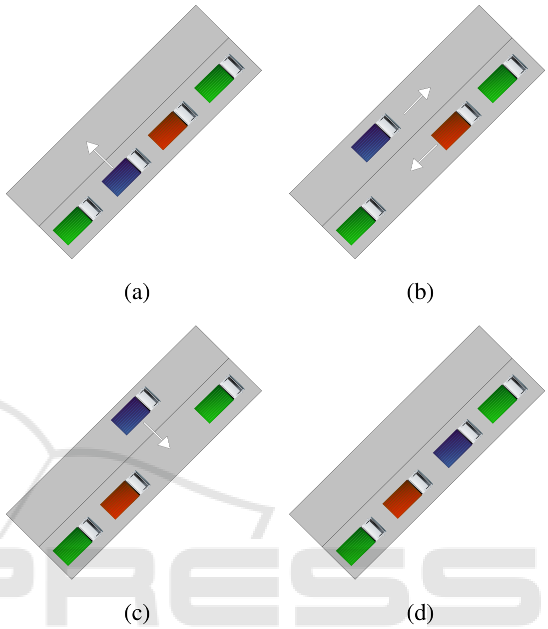

Figure 1: Overtaking maneuver with position constraints.

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3 CASE STUDY

In the following, a four-vehicle platoon is considered ($M = 4$). Vehicle #2 and vehicle #3 are involved in the swap, while the first and the last vehicle of the platoon are assumed to proceed around the regime speed $v_{reg} = 22[m/s]$. The four-vehicle platoon represents the most reasonable choice whereas what it happens it that two trucks exchange their position and they have to pay attention to adjacent elements of the platoon. In more numerous platoons, the four-vehicle subset can be taken into account by the controller only for the time needed to perform the maneuver, while maintaining other elements at constant speed.

The maneuver must ensure the safety of the whole system, so between adjacent elements must intervene a minimum distance, computed as in (Bozzi et al., 2021). According to this formulation, the minimum and the recommended distances are:

$$\begin{aligned} d_{min}[m] &= \frac{3 * v_{reg}[km/h]}{10} = 23.76m \\ d_{opt}[m] &= (\frac{v_{reg}[km/h]}{10})^2 = 62.73m \end{aligned} \tag{5}$$

However, these bounds might even be reduced considering the faster reaction time of unmanned vehicles with respect to human-driven ones. Even if there are other rules to compute the optimal inter-vehicle distance, such as the one stated by the Responsibility Sensitive Safety (RSS) widely used in literature (e.g. in (Shalev-Shwartz et al., 2017) and (Gassmann et al., 2019)), it is useful to start with the recommended distances stated by the traffic regulations which represent the minimum constraints to satisfy within the road nowadays. Of course, assuming only unmanned vehicles it can emerge the possibility of taking into account shorter inter-vehicle distances.

The case study considers an initial inter-vehicle span of $d = 30[m]$, close to the critical bound (d_{min}) and thus representing a risky situation to perform an overtaking maneuver between inner element of the platoon. In the first 5 seconds of the simulation vehicles move at regime and vehicle #3 changes lane in order to proceed with the overtaking maneuver. Re-entering the lane is assumed to be done in the last 5 seconds of simulations, without altering the longitudinal displacement.

The inter-vehicle distance should remain unchanged at the end of the driving routine. Moreover, vehicles involved in the swap should not get too closer to other elements of the platoon (i.e. the leader for vehicle #3, the last element for vehicle #2).

The performance of a PID controller on the continuous nonlinear system are presented and then compared to a control algorithm that deals with the linear discrete approximation of the Lomonossoff's model and makes usage of a LQT problem to compute the optimal control input.

3.1 Nonlinear System

The control of the nonlinear system is governed by a PID that acts converting the desired value in position in a corresponding value in tractive effort. Each vehicle that needs to alter its speed from the regime has its own PID. The only communication that occurs between vehicles involves the message with the actual position, in order for the PID to formulate the proper control action to pursue the desired value. In fact, the desired position is expressed in terms of the actual position, the position of the leader or the position of the last element of the platoon (respectively for vehicle #3 and vehicle #2) and the interdistance between adjacent elements, computed as a function of the regime speed. At each sampling instant k, it can be expressed as follows:

$$\begin{cases} x_2^d(k) = x_1(k) - 2d \\ x_3^d(k) = x_4(k) + 2d = x_1(k) - d \end{cases} \tag{6}$$

Table 2: PID coefficients.

Proportional	2.754
Integral	0.484
Derivative	2.986
Filter coefficient	9.300

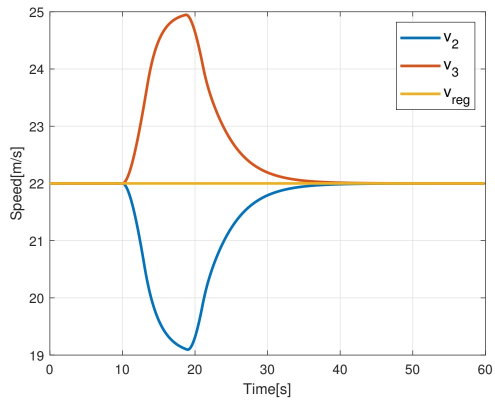

Figure 2: Vehicles' speed: nonlinear system.

Reference trajectory of vehicle #3 should be written with respect to the position of the leader, since unexpected behavior can arise when dealing with a large scale platooning, as demonstrated in (Pates et al., 2017). In this paper, though, considering the small number of vehicles involved in the platoon, both formulations give the same results.

The parameters of the continuous time PID has been tuned using the Matlab/Simulink tool and linearizing the plant near the equilibrium point obtained with the regime speed. Thus, unexpected behaviour may emerge at very different speeds from the initial one. The value used for the simulation are listed in Table 2. The filter coefficient is needed to improve the action of the derivative term, not implemented as a pure derivative because of its sensitiveness to noise. Rate limiter has been added to avoid abrupt changes between consecutive sampling instants, while output saturation is needed to maintain vehicle around its equilibrium point and increase the overall realism of the control input on the virtual environment. Fig. 2 shows the trend of the velocities. As expected, there is a slight acceleration from the third vehicle, while the other starts decelerating to favor the overall maneuver. The behavior is almost specular as both vehicles have the same PID gains and their desired positions are symmetric with respect to the center of platoon.

Fig. 3 confirms the effectiveness of the nonlinear controller, as the distance between vehicles varies according to the expectation and it settles on multiples of 30 meters (based on the pair of vehicles analyzed), ensuring that the initial inter-vehicle distance is maintained.

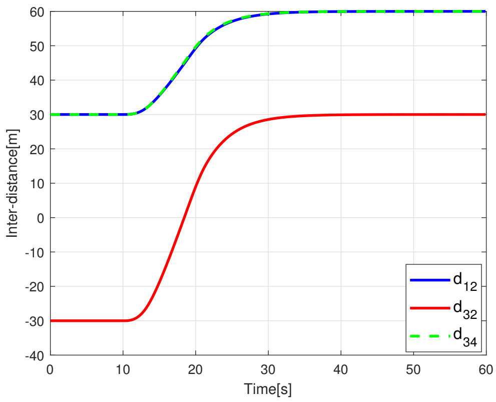

Figure 3: Inter-vehicle distances: nonlinear system.

It can be stated that the objective is achieved smoothly and fastly, without abrupt changes in acceleration and thus preserving passenger's comfort.

3.2 Linear Controller

The linear controller is more complex to implement for many factors: first of all, it relies on time-variant information from the system. Second, it operates on a discretized model which represents an approximation of the actual system. As a matter of fact, the state of the vehicle is used to determine the linearized system around the working point $v(\bar{t}_p)$ and to provide the state for the LQT problem to be solved. For this reason, it is assumed that the trends of the velocities for the nonlinear evolution is known, as it will be used as reference signal to be followed by the tracking algorithm.

The knowledge of velocity trends is a strong assumption, but it is reasonable as the behavior depends on the actual speed of the vehicles. Thus, it is possible to have a set of different maneuvers based on the initial regime speed of the other vehicles of the platoon.

The LQT requires a cost function in order to prioritize the tracking of certain state variables and the cost of the control action. For the case study, the overall cost function for each sampling instant k is:

$$J = \sum_{i=1}^{M}\sum_{k=1}^{K}\left(\alpha_i(x_i(k) - x_i^d(k))^2 + \beta_i(v_i(k) - v_{reg})^2 + \gamma_i f_i(k)\right) + \sum_{i=1}^{M}\left(\alpha_i(x_i(K+1) - x_i^d(K+1))^2 + \beta_i(v_i(K+1) - v_{reg})^2\right) \quad (7)$$

With α, β and γ gains to be tuned to prioritize the respective elements of the summation and K the control horizon for the LQT problem. The higher the K, the smoother but less responsive the reaction of the system. In the case study it has been chosen $K = 10$ not to overburden the computational cost. x_i^d are retrieved as in (6) for vehicles involved in swap, and computed as constant displacement between consecutive sampling instants for outer vehicles. v_{reg} is the regime speed, in the case study equals to $22m/s$ for each element of the platoon.

More in detail the first term is the quadratic deviation from the desired trajectory, which for inner vehicles x_i^d is computed as in (6) and for outer vehicles is not considered (i.e. $\alpha_1, \alpha_4 = 0$), the second term is the deviation from the desired speed and their trend is supposed to be known, and the last term regards the minimization of the input which translates in the minimum tractive effort to be applied to accomplished the goals. The second summation is needed to represent the final control instant for the state.

The equivalent of the cost function in matrix form to be prompted to the LQT is:

$$Q = \begin{bmatrix} \alpha_3+\alpha_2 & 0 & -\alpha_2 & 0 & -\alpha_3 & 0 & 0 & 0 & -\alpha_3 d - 2\alpha_2 d \\ 0 & \beta_1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ -\alpha_2 & 0 & \alpha_2 & 0 & 0 & 0 & 0 & 0 & 2\alpha_2 d \\ 0 & 0 & 0 & \beta_2 & 0 & 0 & 0 & 0 & -\beta_2 v_{reg} \\ -\alpha_3 & 0 & 0 & 0 & \alpha_3 & 0 & 0 & 0 & \alpha_3 d \\ 0 & 0 & 0 & 0 & 0 & \beta_3 & 0 & 0 & -\beta_3 v_{reg} \\ 0 & 0 & 0 & 0 & 0 & 0 & \alpha_4 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & \beta_4 & 0 \\ -\alpha_3 d - 2\alpha_2 d & 0 & 2\alpha_2 d & -\beta_2 v_{reg} & -\alpha_3 d & -\beta_3 v_{reg} & 0 & 0 & 0 \end{bmatrix}$$

$$R = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix} \quad (8)$$

Note that $Q \in \mathbb{R}^{2M+1}$ and $R \in \mathbb{R}^{M+1}$ due to non quadratic terms present in the cost function that require to increase the size of the matrix and the state vector, as explained in (Boyd, 2008).

It is clear that the control technique is centralized, thus the state of the system is composed by all vehicles belonging to platoon, even the ones that have to proceed at constant speed. This centralization ensures the optimal behavior from the platoon's point of view, disregarding the individual element favoring the overall safety of the system.

In the case study, it has been decided to greatly privilege the tracking of speeds over the control cost, setting high β gains. It has to be noted that, if all α gains are set to zero, the platoon control problem translates into M control problems concerning the individual vehicle, as there are no constraints related to inter-vehicle distance.

This turned out to be necessary since with unitary gains the control technique is not able to perform the swap between vehicles. This is shown in Fig.4 and happens because, with unitary gains, for the control algorithm is not convenient to perform the maneuver due to the cost of the input.

On the other hand, if huge importance is given to the maneuver (i.e. gains to track velocity trends are

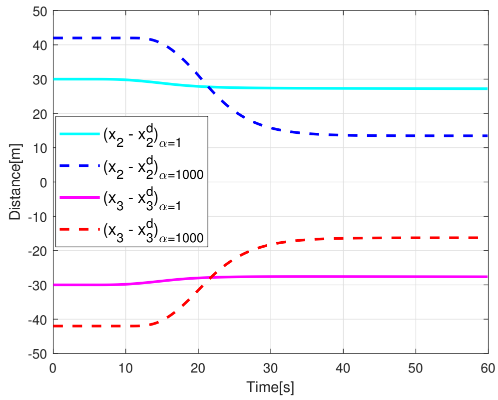

Figure 4: Difference between actual and desired position with $\alpha = 1$ and $\alpha = 1000$.

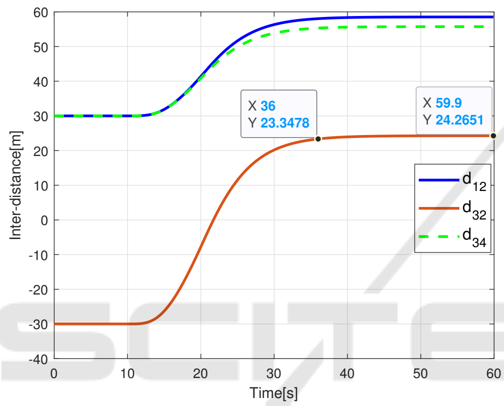

Figure 5: Inter-vehicle distances: linear controller.

significantly higher than gains for the control cost) the inter-vehicle distance evolves as shown in Fig.5, with two markers to point out the behaviour in the middle of the simulation and its final value.

The overall objective is achieved, even if vehicles experiment little reductions in their interdistances. This does not affect safety of the whole system, since each element preserves a distance greater than d_{min} with the following vehicle (very close to the minimum bound for the ones involved in the swap). This is even more valuable considering the high regime speed and the unfavorable initial conditions that should not suggest such a maneuver. Increasing the initial span produces safer results as vehicles have more space in which to exchange. Moreover, the input prompt reported in Fig. 6 highlights the difference between the nonlinear case, in which the output reach its saturation, and the linear evolution, closer to the regime and desired value, improving the fuel consumption overtime.

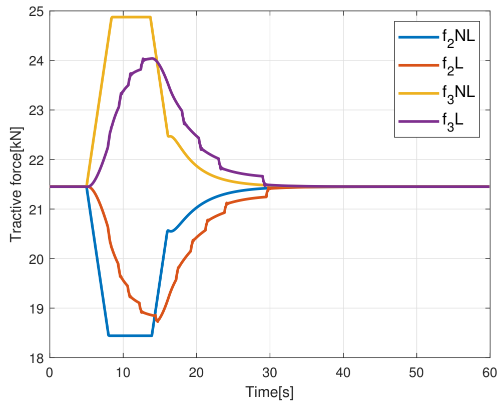

Figure 6: Control action for vehicles involved in the swap.

4 CONCLUSION

This paper analyzes the swap of inner elements of a four-vehicle platoon moving on a straight path. The work shows a comparison between PID controller on nonlinear continuous system and LQT controller on a discretized linear system. A case study for vehicles proceeding at medium speed is presented and analyzed. Even if it is possible, after a correct tuning of PID and gains, to perform the exchange at higher velocity, it is not recommended for safety reasons. In addition, the benefits produced by such driving routing are detectable mainly on heavy-duty vehicles, that do not travel at higher speed.

To conclude, it can be asserted that the driving maneuver can be fluently completed by means of the decentralized controller. It acts on the nonlinear continuous system guaranteeing passengers' comfort and safety, although it requires an accurate tuning of the PID parameters to work properly.

Even with the linear controller, though, vehicles can successfully achieve the swap without endangering the whole system, also when initial conditions are not favourable for this maneuver and suggest a more cautious drive. There still is an offset in the steady state interdistance, that may be refined by low-level controllers to be activated once the system is reaching its regime. Moreover, the tuning can be done more roughly by prioritizing the velocity constraints over the position ones. For these reasons and considering the linearity of the controller and its action on a simplified model of the system, the results obtained on the nonlinear model are satisfactory.

Its main drawback is the need for a priori information that may not be available at the beginning of the maneuver. For future improvements, we surely aim to provide a method to dynamically generate velocity trends to accomplish the driving routine.

It is also worth analyzing an overtaking maneuver that involves more than two vehicles, to fasten the reaching of the optimal string formation in bigger platoons, though it may require too much time to be accomplished even in a free highway road. However, its feasibility will be studied in further works.

Instead, there is no need to test the algorithm at much higher speed ($> 100km/h$), since its advantages are relevant especially for heavy-duty vehicles that should not travel and even perform overtaking maneuver at those velocities.

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