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Multiple-Lane Vehicle Platooning based on a Multi-Agent Distributed Model Predictive Control Strategy*

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***Abstract*—Vehicle platooning became an interesting topic in the last years, many researchers and practitioners from the academia and industry trying to develop new theories and design appropriate control methods and communication methodologies in order to bring this concept as fast as possible on the roads. Since vehicles drive on multi-lane roads and highways, the subsequent paradigm was to treat vehicles as swarms, i.e., groups of vehicles that travel closely together on different lanes and are electronically connected. A step forward towards this new concept would be the design of multiple-lane platoons. As such, this paper proposes a multi-agent distributed model predictive control strategy for the longitudinal coordination of the vehicles in individual platoons and a classical PI control algorithm for the lateral control of each vehicle in the platoon w.r.t. its neighbors. The simulation results obtained in Matlab/Simulink and the performance analysis prove that the concept is viable.**

***Index Terms*—Vehicle platooning, Multiple-lane platooning, Distributed control, Model predictive control**

I. Introduction

The first idea of vehicle platooning, which basically became its first definition, was published in [1]: "*A platoon is a collection of vehicles that travel close together, actively coordinated in formation.*" Although this definition is very general, it does not provide too much information about how the vehicles are inter-connected and how they are supposed to travel together in a formation. A more suitable and specific definition, which is preferred in the literature, was provided while developing the Safe Road Trains for the Environment (SARTRE) platooning concept [2]: "*A platoon is a number of vehicles that are traveling together and electronically connected. There is one lead vehicle and one or more following vehicles. The following vehicles of a platoon are controlled autonomously, while the lead vehicle is controlled manually.*" As mentioned in the latter definition, the biggest interest in platooning appeared with the development of electronic communication channels - Vehicle to Vehicle (V2V) and Vehicle to Infrastructure (V2I) based on wireless connections.

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Vehicle platooning became very popular during the last years, many researchers, both from industry and academia, and from all over the world, trying to pursue the goal of making the highways safer, while increasing their capacity. Moreover, several projects dealt with the vehicle platoon concept, from which the most known are: SARTRE (Europe) [3], California Partners for Advanced Transit and Highways Program (PATH - USA) [4], SCANIA platooning (Europe and Japan), Energy Intelligent Transportation Systems (ITS - Japan), AUTO21 Collaborative Driving System (CDS - Canada) and many others. These projects cannot be compared because they differ in specific parts, but all of them are proving positive effects of platooning concept on highway traffic. The SARTRE project [3] aimed at creation of road trains with a lead commercial vehicle and a set of following vehicles driving in a line. The PATH program published an estimation of 20% decrease of fuel consumption [4]. Also, smaller spacing can be achieved by using platooning, various use-cases and traffic conditions being simulated and feasibility of using road trains was proven.

The most widely studied platoon configuration is the column, also known as train configuration. This arrangement is mostly adapted to urban or highway transportation. Other kinds of formations can be considered, such as line, echelon and arbitrary [5]. Each one of these configurations possesses interesting properties in relation with application fields such as vehicle swarming, which is an optimized platooning method of a swarm of automated vehicles; this is to ensure that the space utilization on highways is optimized and that the traffic congestion is reduced. The configuration considered in this study is a multiple-lane platoon that is composed of several longitudinal platoons with train configurations (each one on a different lane) and for which lateral control is also ensured on a single vehicle basis. Thus, every following vehicle needs to maintain a safe distance w.r.t. the vehicle in front and the lateral vehicles (in the right and/or left side). In particular, the leading vehicles from each lane must only keep the desired lateral distance in between themselves.

Due to the intrinsic coupling within the multiple-lane platoon, this kind of system can be regarded as a collection of different sub-systems (i.e. the vehicles) coupled among each others. As such, a reasonable control choice is the distributed model predictive control strategy (DMPC) [6], [7]. The working idea is to locally control each vehicle by a local agent (or controller) taking into account the coupling nature between the sub-systems (e.g. caused by dynamics, optimization problems and / or constraints). In [8], a DMPC strategy for active steering of a cooperative vehicle platoon is proposed, whereas a non-cooperative DMPC algorithm for the longitudinal control in a platoon is given in [9]. The cruise and headway control of a in-line vehicle platoon is provided in [10], where the overall string stability is ensured via appropriate terminal constraints selection.

This work proposes a general framework to model and control the vehicles in a multiple-lane platoon considered as a multi-agent system. As such, a multi-agent distributed model predictive control strategy is designed for the longitudinal coordination of the vehicles in individual platoons and a classical proportional-integral (PI) controller algorithm is designed for the lateral control of each vehicle in the platoon w.r.t. its neighbors.

The paper is structured as follows. Section II presents the longitudinal and lateral models of the vehicle used in Section III for controller design purposes. In Section IV the simulation results are illustrated with a performance analysis, followed by the concluding remarks in Section V.

II. Vehicle dynamics modeling

In what follows, the longitudinal and lateral models of the vehicle, used in Section III for controller design purposes, are briefly described.

A. Longitudinal dynamics

In this subsection, the longitudinal dynamics corresponding to each vehicle in the platoon is given. From control design considerations, the vehicle model is reduced only to the automotive drive-train, which is a mechanical system that describes the power transfer from the engine to the driving wheels. Still, this dynamics simplification needs to provide a sufficiently complex model to characterize the main dynamics of the drive-train [11].

In Fig. 1 a schematic diagram for the drive-train dynamics is given, which is described by two inertias linked by a flexible drive-shaft. The first inertia J_{eg} models the engine, the gearbox and the final reduction gear (FRG), whereas the second one J_v represents the driving wheels and vehicle cumulative influences.

Within this model, the torque generated by the engine, denoted T_e, acts as the control variable and is presumed to be produced instantaneous, whenever the engine electronic control unit (ECU) requests it. The dynamics involved in the torque production, i.e., combustion and airflow control is not within the scope of this work and is available in [12].

The engine-gearbox inertia is described as:

$$J_{eg}\dot{\omega}_e = T_e - b_e\omega_e - T_f/i_{\text{tot}}, \tag{1}$$

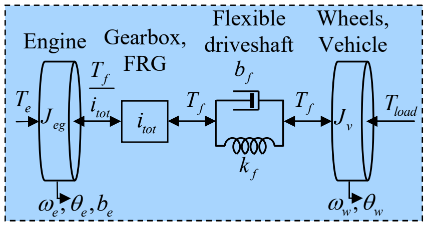

Fig. 1. Vehicle drive-train schematic representation.

where the corresponding inertia of the engine-gearbox ensemble is denoted by $J_{eg} := J_e + \frac{J_g}{i_{\text{tot}}^2}$, depending on $i_{\text{tot}} = i_g i_f$, which is the overall transmission ratio from the gearbox and the FRG, and both the engine J_e and the gearbox J_g inertias, respectively; the speed and the damping coefficient of the engine are marked with ω_e and b_e, jointly; the torque in the flexible drive-shaft is expressed by T_f.

The wheel-vehicle inertia is modeled by:

$$J_v\dot{\omega}_w = T_f - T_{\text{load}}, \tag{2}$$

with the wheel speed ω_w and the load torque T_{load}. Subsequently, the vehicle inertia is given by:

$$J_v = J_w + m_v r_w^2, \tag{3}$$

where J_w defines the wheels inertia, and the equivalent longitudinal inertia of the vehicle mass depends on the mass of the vehicle m_v and the wheel radius r_w.

In order to define the torque in the flexible drive-shaft, one can express it as a spring and damper mechanism:

$$T_f = b_f\left(\omega_e/i_{\text{tot}} - \omega_w\right) + k_f\left(\theta_e/i_{\text{tot}} - \theta_w\right), \tag{4}$$

with k_f and b_f the elasticity and the damping coefficients, respectively; θ_e and θ_w are the engine and wheel angles, jointly.

The load torque

$$T_{\text{load}} = T_{\text{airdrag}} + T_{\text{roll}} + T_{\text{grade}}, \tag{5}$$

is computed as sum of three torque components corresponding with:

i) the aerodynamic drag of the vehicle
$T_{\text{airdrag}} = 0.5\rho_{\text{air}} A_f c_d V_x^2 r_w$,

with ρ_{air} the air density, A_f the frontal area of the vehicle, c_d the airdrag coefficient and V_x the vehicle speed. Since $V_x = r_w\omega_w$ it implies that T_{airdrag} is a nonlinear in ω_w, which can be approximated with

$$T_{\text{airdrag}} = b_a\omega_w, \tag{6}$$

where b_a is an approximation parameter.

ii) the rolling of the tires
$T_{\text{roll}} = c_r m_v g\cos(\chi_{\text{road}}) r_w$

where c_r denotes the rolling coefficient, g is the gravitational acceleration and χ_{road} is the road grade.

iii) the road grade
$T_{\text{grade}} = m_v g\sin(\chi_{\text{road}}) r_w$.

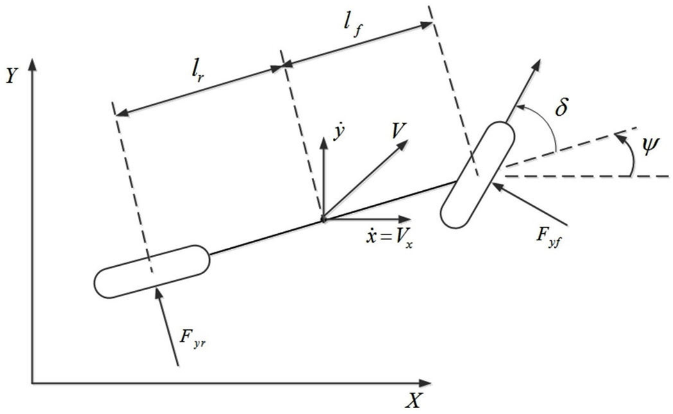

Fig. 2. Bicycle model of a vehicle.

The engine torque (control input) is restricted by lower and upper bounds, i.e.,

$$0 \leq T_e \leq T_e^{max}, \tag{7}$$

where T_e^{max} is the maximum torque that can be generated by the internal combustion engine.

The output of the longitudinal dynamics is selected as the vehicle speed V_x, which can be determined directly from the wheel speed as mentioned previously.

B. Lateral dynamics

To implement the control strategy for lane keeping, a lateral dynamics model of the vehicle is needed. Usually, the vehicle dynamics is modeled using the *bicycle model* or *single track model* (Fig. 2), which considers the front wheels united and the same for the back wheels of the vehicle. Moreover, the vehicle's center of gravity is considered to be at the ground level, thus ignoring the influences of vehicle tilting on the lateral and longitudinal dynamics.

The mathematical model can be obtained using Newton's second law of movement, yielding:

$$\begin{aligned} m_v\ddot{x} &= m_v\dot{y}\dot{\psi} + 2F_{xf} + 2F_{xr}, \\ m_v\ddot{y} &= -m_v\dot{x}\dot{\psi} + 2F_{yf} + 2F_{yr}, \\ J\ddot{\psi} &= 2l_fF_{yf} - 2l_rF_{rf}, \end{aligned} \tag{8}$$

where x is the longitudinal position and y is the lateral position of the vehicle, respectively, ψ is the vehicle yaw angle, F_{xf} and F_{xr} are the longitudinal tire forces of the front and rear wheels, respectively, F_{yf} and F_{yr} are the lateral tire forces of the front and rear wheels, respectively, l_f and l_r are the distances between the front axle and the rear axle, respectively, and the center of gravity, and J is the lateral vehicle inertia.

The tire forces (F_{xf}, F_{xr}, F_{yf} and F_{yr}) are responsible for the vehicle movement and can be modeled using Pacejka's nonlinear model [13], as:

$$\begin{aligned} F_{xf} &= f_{xf}(\alpha_f, \kappa_f, F_{zf}),\ F_{xr} = f_{xr}(\alpha_r, \kappa_r, F_{zr}), \\ F_{yf} &= f_{yf}(\alpha_f, \kappa_f, F_{zf}),\ F_{yr} = f_{yr}(\alpha_r, \kappa_r, F_{zr}), \end{aligned} \tag{9}$$

where α_f is the front wheels slipping angle, α_r is the back wheels slipping angle, κ_f is the front wheels longitudinal slipping, κ_r is the back wheels longitudinal slipping, F_{zf} and F_{zr} are the normal forces that act on the front axle and rear axle, respectively.

The wheels slipping angles from (9), can be computed as:

$$\tan\alpha_f = \frac{-\dot{x}\sin\delta + (\dot{y} + l_f\dot{\psi})\cos\delta}{\dot{x}\cos\delta + (\dot{y} + l_f\dot{\psi})\sin\delta}, \tan\alpha_r = \frac{\dot{y} - l_r\dot{\psi}}{\dot{x}}, \tag{10}$$

where δ is the steering angle of the front wheels.

To calculate the longitudinal slipping of the front and rear wheels, respectively, taken into account in (9), a difference between acceleration (a) and braking (b) must be considered as (for the front wheels):

$$\kappa_{a,f} = -\frac{\dot{x} - r_w\omega_{w,f}}{r_w\omega_{w,f}},\ \kappa_{b,f} = -\frac{\dot{x} - r_w\omega_{w,f}}{\dot{x}}, \tag{11}$$

where $\omega_{w,f}$ is the angular speed of the front wheel. The longitudinal slipping parameters for the back wheels $\kappa_{a,r}$ and $\kappa_{b,r}$ can be determined in a similar manner.

Considering that the vehicle drives on a perfectly flat road, the normal forces F_{zf} and F_{zr} are given as:

$$F_{zf} = \frac{m_v g l_r}{2(l_f + l_r)},\ F_{zr} = \frac{m_v g l_f}{2(l_f + l_r)}. \tag{12}$$

The equations described by (8) - (12) represent the mathematical model of the vehicle dynamics, which is nonlinear, but it can be generally linearized in order to control just the lateral or the longitudinal dynamics and we'll consider just the lateral dynamics control in what follows.

A linear model of the lateral dynamics can be obtained by linearizing the front and rear tires lateral forces:

$$F_{yf} = C_{yf}\alpha_f,\ F_{yr} = C_{yr}\alpha_r, \tag{13}$$

where C_{yf} and C_{yr} are the cornering stiffness coefficients of the tires.

The slipping angles α_f and α_r can be rewritten using the small angles approximations as:

$$\alpha_f = \delta - \frac{\dot{y} + l_f\dot{\psi}}{\dot{x}},\ \alpha_r = -\frac{\dot{y} - l_r\dot{\psi}}{\dot{x}}. \tag{14}$$

Considering that the vehicle has a constant longitudinal speed V_x, the equations given in (8) can be reduced to describe only the lateral dynamics as:

$$\begin{aligned} m_v\ddot{y} &= -m_vV_x\dot{\psi} + 2F_{yf} + 2F_{yr}, \\ J\ddot{\psi} &= 2l_fF_{yf} - 2l_rF_{rf}, \end{aligned} \tag{15}$$

where δ is the control input and y is the output of the system.

III. Multiple-lane platooning control strategy

To achieve the multiple-lane vehicle platooning aim, the control problem was split in two stages: *A)* single-lane platoon control based on a DMPC strategy and *B)* lateral control characteristics for individual vehicles within the platoon based on a PI control strategy.

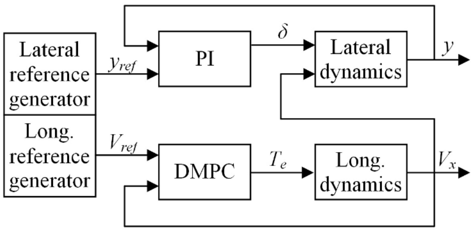

Fig. 3. Control architecture for a leader in the multiple-lane platoon.

A. Control architecture

Each leader vehicle uses a model predictive control strategy, as detailed in the following subsection, to maintain a certain reference speed V_{ref}. This reference is provided either by the driver, or by another controller superior in the hierarchy, e.g., smart infrastructure, adaptive cruise control, which is denoted as the *Longitudinal reference generator* in Fig. 3, by manipulating the engine torque T_e. Moreover, the leading vehicles from each lane must also keep the desired lateral distance between themselves, which is directly related to their imposed lateral position y_{ref} provided by the *Lateral reference generator*. This action is performed by manipulating the steering angle δ using a PI controller (see Fig. 3). Note that the vehicle speed V_x is needed as an input for the lateral dynamics.

A similar architecture as the one detailed for the leaders (Fig. 3) is required for the followers. Every following vehicle needs to maintain a safe distance w.r.t. the vehicle in front by using a DMPC strategy as it will be presented in the following subsection and a safe distance w.r.t. the lateral vehicles (in the right and/or left side) using a PI controller.

B. DMPC longitudinal control for vehicle platooning

In this subsection some details regarding the DMPC algorithm are provided. As previously mentioned, this strategy is suitable for multiple, coupled sub-systems, since the interactions are considered directly into the optimization problem.

From the vehicle platooning point of view, we propose a non-cooperative, non-iterative strategy, formulated for input-coupled sub-systems. For the particular train (or in-chain) communication architecture, the relevant information is uni-directionally broadcast from the agent in charge of the leading vehicle, hereafter named the platoon leader towards the controller which regulates the next following vehicle, called follower. At the local level, this agent uses the data to compute the optimal solution for the locally described optimization problem and sends the corresponding knowledge towards its follower agent. The algorithm is non-iterative, since among two consecutive agents, the information is exchanged only once within the sampling period.

The control objectives for the longitudinal vehicle platooning problem, with train configuration are defined separately, namely: *i) cruise control* (i.e. tracking an imposed velocity reference) for the leader and *ii) headway control* (i.e. maintaining a desired distance) for the followers. In the latter, a time variant headway control was imposed, using the methodology from [14]:

$$S_d = S_0 + hV_{xf} \tag{16}$$

with S_d is the desired headway between the followers, S_0 is the minimum inter-vehicle distance allowed and V_{xf} is the follower's velocity; h is a function of the relative velocity, defined as:

$$h = \begin{cases} \alpha V_{xf}, \quad h_0 - c_0(V_{xl} - V_{xf}) \geq \alpha V_f \\ h_0 - c_0(V_{xl} - V_{xf}), \quad 0 \leq h_0 - c_0(V_{xl} - V_{xf}) \leq \alpha V_{xf} \\ 0, \quad \text{otherwise} \end{cases} \tag{17}$$

where V_{xl} is the velocity of the 'relative' leader, i.e. the predecessor of the current follower; $h_0 > 0$, $c_0 > 0$ are two constants to manipulate the influence of the relative velocity $V_{xl} - V_{xf}$; and $\alpha > 0$ is used to compute the maximum saturation value for h, depending on the current follower's velocity V_{xf}. Note, that in particular, for $h = 0$ the imposed headway S_d is reduced to the minimum distance S_0 allowed between the vehicles, whereas with $S_0 = 0$ the desired distance is solely influenced by V_{xf}.

Starting from a vehicle longitudinal dynamics given in Section II-A and using $\gamma = T_e$ as the control input and $\upsilon = V_x = r_w\omega_w$ as the measured output, hereafter the $\mathcal{N}$ vehicles platoon is described, where each vehicle $i \in \mathcal{N}$ has the following linearized first order model:

$$\dot{V_x} = \frac{1}{\tau}V_x + \frac{K}{\tau}T_e \tag{18}$$

where τ is the time constant and K is the gain of the system.

In the corresponding state-space model, the longitudinal vehicle position x_l, and the forward velocity V_{xl} are the components of the state vector ξ_l, while γ_l and υ_l are the manipulated and output variables, respectively:

$$\begin{aligned} \dot{\xi_l} &= \begin{bmatrix} 0 & 1 \\ 0 & \frac{-1}{\tau_1} \end{bmatrix} \xi_l + \begin{bmatrix} 0 \\ \frac{K_l}{\tau_l} \end{bmatrix} \gamma_l \\ \upsilon_l &= \begin{bmatrix} 0 & 1 \end{bmatrix} \xi_l \end{aligned} \tag{19}$$

where l subscript denotes the leader.

In order to create a input-coupled platoon from individual vehicles defined with (19), each follower was modeled as in [10]:

$$\begin{aligned} \dot{\xi_f} &= \begin{bmatrix} 0 & -1 & 1 \\ 0 & \frac{-1}{\tau_f} & 0 \\ 0 & 0 & \frac{-1}{\tau_l} \end{bmatrix} \xi_f + \begin{bmatrix} 0 \\ \frac{K_f}{\tau_f} \\ 0 \end{bmatrix} \gamma_f + \begin{bmatrix} 0 \\ 0 \\ \frac{K_l}{\tau_l} \end{bmatrix} \gamma_l \\ \upsilon_f &= \begin{bmatrix} 1 & 0 & 0 \end{bmatrix} \xi_f \end{aligned} \tag{20}$$

where the state vector ξ_f consists of the headway with respect to its 'relative' leader (i.e. the vehicle in front, denoted with l subscript) and the forward velocities V_{xf} and V_{xl} of the current follower and its predecessor, respectively; γ_f and υ_f have the same meaning as in (19), the f subscript denoting the follower.

Note that in (20), the followers are input-coupled with their leaders through the exogenous input γ_l which is received from the vehicle in front.

In order to ensure that the tracking problem for both leader and followers does not have steady-state error, the prediction models were augumented with an integrator, using the modeling methodology described in [9]. After that, for each agent $i \in \{2, \ldots \mathcal{N}\}$ in charge of each follower, the local cost function proposed in [9] was used:

$$\begin{aligned} J_i(\xi_i(k), \Delta\Gamma_i(k), \Delta\Gamma_{i-1}(k)) = \\ (R_{si} - \Upsilon_i)^T (R_{si} - \Upsilon_i) + \Delta\Gamma_i(k)^T R_i \Delta\Gamma_i(k) \end{aligned} \tag{21}$$

with Υ_i output predictor defined over the prediction horizon N_p; $\Delta\Gamma_i(k)$ the local future input sequence computed over the control horizon ($N_c \leq N_p$); $R_{si} \in R^{N_p}$ is the set-point vector and $R_i = \beta I_{N_c}$, $\beta \geqslant 0$ defines the input weight matrix; $\Delta\Gamma_{i-1}(k)$ is the input trajectory received from the previous vehicle via the communication network.

Notice that the leader's cost function, with subscript $i = 1$ defined with (21) is not influenced by $\Delta\Gamma_{i-1}(k)$ since the first vehicle in the platoon can be treated independently of the following vehicles.

For all vehicles in the platoon, the local cost functions were minimized taking into account input constraints (7) rewritten as:

$$0 \leq \Delta\Gamma_i(k) \leq \gamma_{\text{max}} \tag{22}$$

where $\gamma_{\text{max}} \in R^{N_c}$ is a vector containing the maximum input value within the control horizon.

C. Lateral control for multiple-lane platooning

For controller design purposes, using (13), (14) and (15), a linear state-space model of the vehicle lateral dynamics can be obtained:

$$\begin{aligned} \dot{z}\,(k) = Az\,(k) + Bu\,(k) \\ t\,(k) = Cz\,(k) \end{aligned} \tag{23}$$

with

$$A = \begin{bmatrix} 0 & 1 & 0 & 0 \\ 0 & -\frac{2C_{yf}+2C_{yr}}{m_v V_x} & 0 & -V_x - \frac{2l_f C_{yf} - 2l_r C_{yr}}{m_v V_x} \\ 0 & 0 & 0 & 1 \\ 0 & -\frac{2l_f C_{yf} - 2l_r C_{yr}}{J V_x} & 0 & -\frac{2l_f^2 C_{yf} + 2l_r^2 C_{yr}}{J V_x} \end{bmatrix},$$

$$B = \begin{bmatrix} 0 \\ \frac{2C_{yf}}{m_v} \\ 0 \\ \frac{2aC_{yf}}{J} \end{bmatrix}, C = \begin{bmatrix} 1 & 0 & 0 & 0 \end{bmatrix}$$

where $z = \left[y, \dot{y}, \psi, \dot{\psi}\right]^T$ is the state vector, $u = \delta$ is the control input and $t = y$ is the output of the system.

Since a highway scenario is considered, the model in (23) was linearized considering a constant speed $V_x = 120$km/h.

Based on the linear state-space model given in (23), a pole placement via state feedback method was applied to design the PI controller.

IV. Illustrative results

In order to test the performances of the proposed control algorithms, a three-lane platoon with three platoons running in parallel on different lanes, each one with one leader and four followers was chosen. As such, a simulator was developed in Matlab/Simulink (Fig. 4) to observe the evolution of the multiple-lane platoon and to test the performances of the proposed control algorithms. In Fig. 5 one can observe the trajectory of each vehicle in the platoon over a simulation of 400s (a small part of it is shown in Fig. 4), from which it can be seen that the lateral control behaves very well. Note that the parameters of the PI controller designed using a pole placement method are: $K_r = 0.2$ and $T_i = 2000$.

For the DMPC longitudinal control, using the parameters from [11], yielded $K = 0.747$ and $\tau = 22.95$ in (18). The control algorithm was designed with a control horizon $N_c = 2$ samples, a prediction horizon $N_p = 15$ samples and using a sampling period $T_s = 0.1$s.

The speeds of the vehicles in the middle-lane platoon are illustrated in Fig. 6 for a variation of the leader speed, in which it can be observed that the speed of the leader is always the highest in module at a certain moment in time. The error between the desired headway given by relation (16), with $S_0 =$ 1m, $h_0 = 0.25$s, $c_0 = 0.01$s and $\alpha = 0.1$s, and the actual headway is illustrated in Fig. 7. It can be seen that the errors decrease along the platoon, which ensures the string stability of the whole platoon. Moreover, in Fig. 8 the applied torques are presented as applied by the vehicles in the middle-lane platoon constrained at $T_e^{max} = 240$Nm.

V. Conclusion

In this paper, a complete framework for multiple-lane platooning was proposed. Firstly, the longitudinal and the lateral dynamics of the vehicle were presented. Then, based on these models, a multi-agent DMPC algorithm was proposed for the longitudinal control problem in a single platoon. This was followed by a classical PI controller was proposed for the lateral control of each vehicle in the multiple-lane platoon. Several simulations realized using a simulator developed in Matlab/Simulink illustrated the performances of the designed multi-lane platoon. It was shown that the lateral control of the vehicles was ensured, while also satisfying the string stability of each individual single-lane platoon.

References

[1] S. Shladover, *Operation of Automated Guideway Transit Vehicles in Dynamically Reconfigured Trains and Platoons: Extended Summary*. U.S. Urban Mass Transportation Administration, Office of Technology Development and Deployment, 1979.

[2] C. Bergenhem, Q. Huang, A. Benmimoun, and T. Robinson, "Challenges of platooning on public motorways," in *17th World Congress on Intelligent Transport Systems*, Busan, South Korea, 2010.

[3] A. Davila, E. del Pozo, E. Aramburu, and A. Freixas, "Environmental benefits of vehicle platooning," in *SAE Symposium on International Automotive Technology*, Pune, India, 2013.

[4] S. E. Shladover, "PATH at 20 History and major milestones," *IEEE Transactions on Intelligent Transportation Systems*, vol. 8, pp. 584–592, 2007.

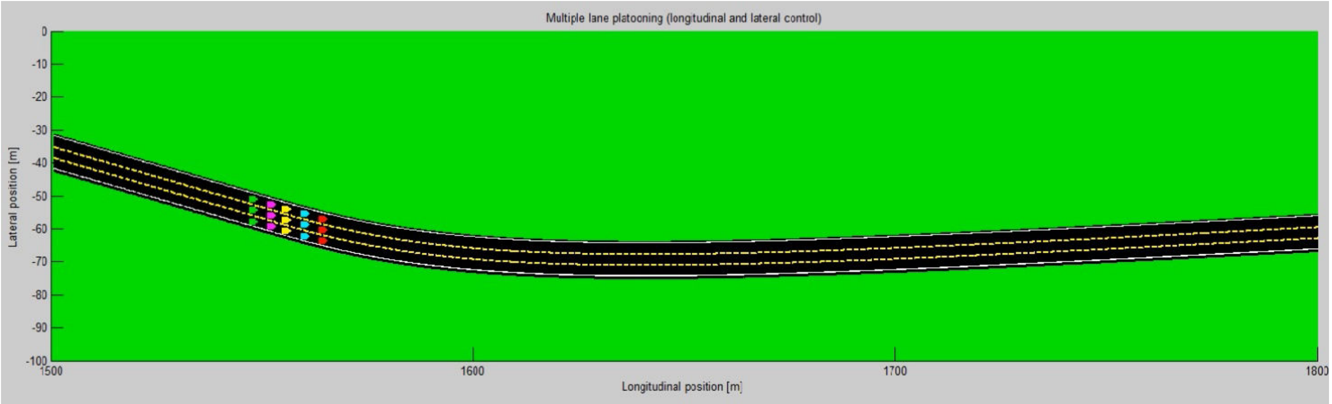

Fig. 4. Screen capture of the multi-lane platoon simulator.

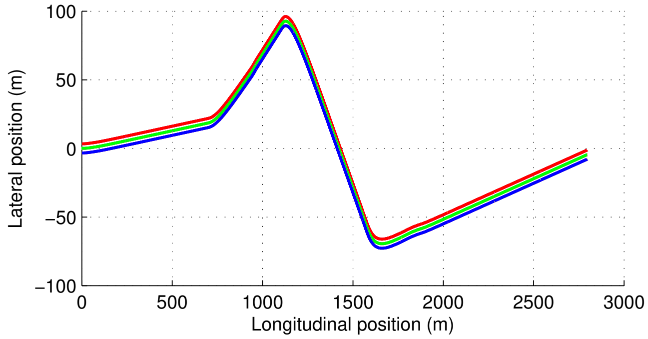

Fig. 5. Positions of the vehicles in the xOy plane.

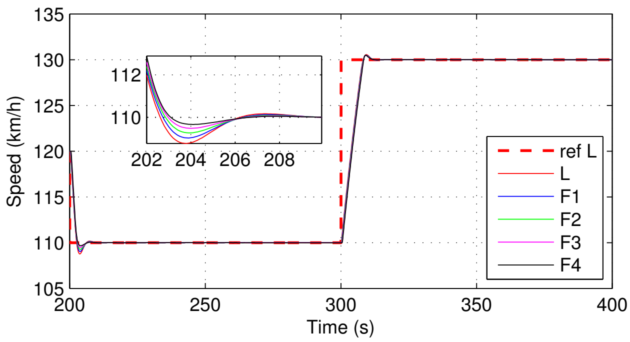

Fig. 6. Speeds of the vehicles in the middle-lane platoon.

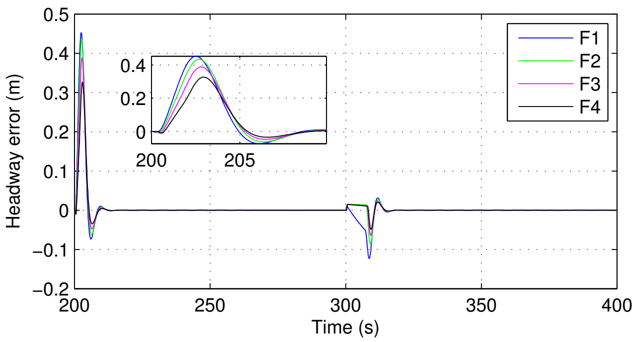

Fig. 7. Headway errors of the follower vehicles in the middle-lane platoon.

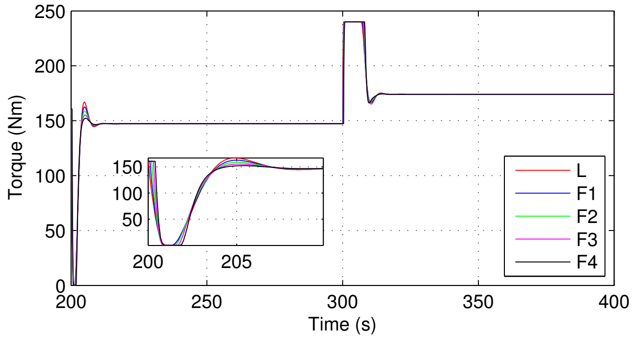

Fig. 8. Torques applied by the vehicles in the middle-lane platoon.

[5] M. El-Zaher, B. Dafflon, F. Gechter, and J.-M. Contet, "Vehicle platoon control with multi-configuration ability," *Procedia Computer Science*, vol. 9, pp. 1503–1512, 2012.

[6] Y. Zheng, S. E. Li, K. Li, F. Borrelli, and J. K. Hedrick, "Distributed model predictive control for heterogeneous vehicle platoons under unidirectional topologies," *IEEE Transactions on Control Systems Technology*, vol. 25, pp. 899–910, 2017.

[7] L. Dai, Q. Cao, Y. Xia, and Y. Gao, "Distributed MPC for formation of multi-agent systems with collision avoidance and obstacle avoidance," *Journal of the Franklin Institute*, vol. 354, pp. 2068–2085, 2017.

[8] R. Kianfar, P. Falcone, and J. Fredriksson, "A distributed model predictive control approach to active steering control of string stable cooperative vehicle platoon," in *7th IFAC Symposium on Advances in Automotive Control*, Tokyo, Japan, 2013, pp. 750–755.

[9] A. Maxim, C. F. Caruntu, and C. Lazar, "Distributed model predictive control algorithm for vehicle platooning," in *20th International Conference System Theory, Control and Computing*, Sinaia, Romania, 2016, pp. 657–662.

[10] ——, "Cruise and headway control for vehicle platooning using a distributed model predictive control algorithm," in *21st International Conference System Theory, Control and Computing*, Sinaia, Romania, 2017, pp. 146–151.

[11] C. F. Caruntu, M. Lazar, S. Di Cairano, R. H. Gielen, and P. P. J. van den Bosch, "Lyapunov based predictive control of vehicle drivetrains over CAN," *Control Engineering Practice*, vol. 21, pp. 1884–1898, 2013.

[12] S. Di Cairano, D. Yanakiev, A. Bemporad, I. Kolmanovsky, and D. Hrovat, "Model predictive powertrain control: an application to idle speed regulation," ser. Lecture Notes in Control and Information Sciences. Springer, 2010.

[13] H. Pacejka, *Tire and Vehicle Dynamics*. Elsevier, 2012.

[14] D. Yanakiev and I. Kanellakopoulos, "Variable time headway for string stability of automated heavy-duty vehicles," in *34th IEEE Conference on Decision and Control*, New Orleans, LA, USA, 1995, pp. 4077–4081.