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Dynamic Speed Limits and On-Ramp Metering for IVHS using Model Predictive Control

Lakshmi Dhevi Baskar, Bart De Schutter, and Hans Hellendoorn

Abstract— **We consider traffic management and control approaches for Intelligent Vehicle Highway Systems (IVHS), which consist of interacting intelligent vehicles and intelligent roadside controllers. The vehicles are organized in platoons with short intraplatoon distances, and larger distances between platoons. All vehicles are assumed to be fully automated, i.e., throttle, braking, and steering commands are determined by an automated on-board controller. We consider both dynamic speed limit control for the platoons in the IVHS and access control at the on-ramps using ramp metering. We propose a model-based predictive control (MPC) approach to determine appropriate speed limits and release times at the on-ramps for the platoons. The proposed approach is also applied to a simple simulation example in which the aim is to minimize the total time all vehicles spend in the network by optimally assigning dynamic speed limits and on-ramp release times.**

I. Introduction

The ever-increasing demand for mobility and transportation results in growing traffic congestion problems throughout the world. On the short term one of the most promising approaches to reduce the frequency and the impact of traffic jams is the use of advanced traffic management and control methods in which control measures such as traffic signals, dynamic route information panels, ramp metering installations, dynamic speed limits, etc. are used to control the traffic flows and to prevent or to reduce traffic jams, or more generally to improve the performance of the traffic system.

Advanced technologies from the field of control engineering, communication, and information technology are currently being combined with the existing transportation infrastructure and equipment. This will result in integrated traffic management and control systems that incorporate intelligence in both the roadside infrastructure and in the vehicles, and that are commonly called Intelligent Vehicle Highway Systems (IVHS) [1], [2].

In IVHS every vehicle contains an automatic system that can take over the driver's responsibilities in steering, braking, and throttle control. This complete automation of driving tasks allows to arrange the vehicles in closely spaced groups called platoons. In the platooning approach cars travel on the highway in platoons with small distances (e.g., 2 m) between vehicles within the platoon, and much larger distances (e.g., 30–60 m) between different platoons. High speeds and short intraplatoon spacings allow more vehicles to be accommodated on the network, which substantially increases the maximal traffic flows [1].

In this paper, we deal traffic congestion problems by using a variant of IVHS in which the monitoring and control handles offered by automated intelligent vehicles (IVs) are combined with those of the roadside infrastructure. In the proposed approach platooning is integrated with conventional traffic control measures such as dynamic speed limits, route guidance, ramp metering, etc. The overall control framework we use is the hierarchical framework we have presented in [3]. We will in particular focus on the control layer that manages the different platoons in the IVHS as well as the access to the IVHS from the non-automated part of the traffic network. More specifically, we will consider how to determine appropriate speed limits for the platoons within the IVHS and appropriate release times of vehicles or platoons that enter the IVHS through on-ramps so as to optimize the performance of the traffic system. Possible performance measures in this context are throughput, travel times, safety, fuel consumption, robustness, etc.

The paper is organized as follows. In Section II we recapitulate the hierarchical IV-based traffic control framework of [3] that will be adopted in this paper. Section III describes the model-based predictive control (MPC) design method that will be used to determine optimal speed limits and on-ramp release times for the platoons. MPC requires prediction models that offer a balanced trade-off between accuracy and simulation speed. In Section IV we discuss some models that could be used in this context. In Section V we apply the proposed approach to a case study based on simulations and we highlight the potential effects of the proposed approach on the traffic flow performance.

II. Hierarchical framework for IV-based traffic management

Now we briefly present the hierarchical control framework for IVHS we have proposed in [3] and which is closely related to the PATH framework [2]. The framework of [3] distributes the intelligence between roadside infrastructure and vehicles, and uses IV-based control measures to prevent congestion and/or to improve the performance of the traffic network. The control architecture of [3] is based on the platoon concept and consists of a multi-level control structure with local controllers at the lowest level and one or more higher supervisory control levels as shown in Figure 1. The layers of the framework can be characterized as follows:

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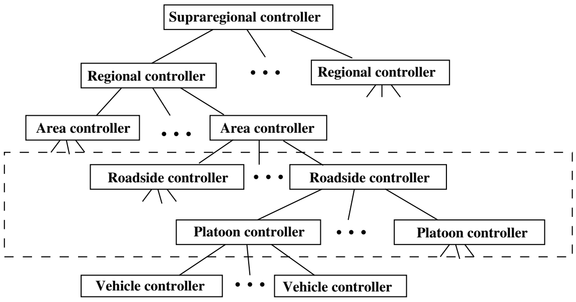

Fig. 1. IV-based framework of [3]. The focus of this paper is indicated by the dashed box.

- The *higher-level controllers* (such as area, regional, and supraregional controllers) provide network-wide coordination of the lower-level and middle-level controllers. The activities of a group of roadside controllers could be supervised by an area controller. In turn, a group of area controllers could be supervised or controlled by regional controllers, and so on.
- The *roadside controllers* use IV-based control measures to improve the traffic flow. Each platoon in the highway network is considered as a single entity by the roadside controller. This significantly reduces the complexity of the control problem compared to the case where each individual vehicle would be controlled by the roadside controller. As a consequence, the whole traffic network can be managed more efficiently.
- The *platoon controllers* receive commands from the roadside controllers and are responsible for control and coordination of each vehicle inside the platoon. The platoon controllers are mainly concerned with actually executing the interplatoon maneuvers (such as merges with other platoons, splits, and lane changes) and intraplatoon activities (such as maintaining safe intervehicle distances).
- The *vehicle controllers* present in each vehicle receive commands from the platoon controllers (e.g., set-points or reference trajectories for speeds, headways, and paths) and they translate these commands into control signals for the vehicle actuators such as throttle, braking, and steering actions.

For a more extensive description of the framework the interested reader is referred to [3].

In the remainder of the paper we focus on the roadside controllers and on their interaction with the platoons and the platoon controllers. The main tasks of the roadside controllers are to assign desired speeds for each platoon, to provide safe distances to avoid collisions between platoons, desired platoon sizes (depending on the traffic conditions), dynamic route guidance for the platoons, ramp metering values at the on-ramps, and also to instruct for merges, splits, and lane changes of platoons. Moreover, we also consider the interface between the IVHS network (i.e., the fully automated road network), and the non-automated road network, where drivers still have full manual control over their vehicle. The interface consists of on-ramps, at which the IVHS control architecture will take over control of the vehicles and arrange them in platoons.

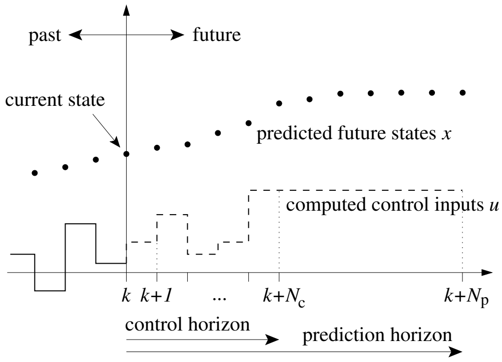

Fig. 2. Prediction and control horizon in MPC.

III. Model predictive control for IV-based traffic management

A. Model predictive control

Model Predictive Control (MPC) [4], [5] has originated in the process industry and it has already been successfully implemented in many industrial applications. MPC makes use of discrete-time models. Let T_ctrl be the control sampling interval, i.e., the time interval between two updates of the control signal settings. At each control step k (corresponding to time $t = kT_\mathrm{ctrl}$), the MPC controller first measures or determines the current state $x(k)$ of the system. Next, the controller uses (on-line) optimization and an explicit prediction model to determine the optimal values for the control measures over a given prediction period determined by the control horizon N_p (see Figure 2). In order to reduce the computational complexity of the problem, one often introduces a constraint of the form $u(k+j) = u(k+j-1)$ for $j = N_\mathrm{c}, \ldots, N_\mathrm{p}-1$, where N_c is called the control horizon.

The optimal control inputs are then applied to the system in a receding horizon approach as follows. At each control step k only the first control sample $u^*(k)$ of the optimal control sequence $u^*(k), \ldots, u^*(k+N_\mathrm{c}-1)$ is applied to the system. Next, the prediction horizon is shifted one step forward, and the prediction and optimization procedure over the shifted horizon is repeated using new system measurements. This receding horizon approach introduces a feedback mechanism, which allows to reduce the effects of possible disturbances and model mismatch errors.

B. MPC for IVHS

We now explain how MPC can be applied for speed control and on-ramp control in IVHS. The roadside controller works with platoons as basic entities. So the state of the system includes the positions and speeds of the platoon leaders and the lengths of the platoons, as well as the number of platoons waiting at the mainstream origins and on-ramps of the IVHS network. The control signal u will consist of the speed limits for the platoon leaders, on-ramp release times, etc.

There exists a wide range of traffic models [6]. An important factor that determines the choice of the model to be used in MPC is the trade-off between accuracy and computational complexity since at each control step k the model will be simulated repeatedly within the on-line optimization algorithm. As a consequence, very detailed microscopic traffic simulation models are usually not suited as MPC prediction model. Instead, simplified or more aggregate models are usually applied. In Section IV we will present some models that are especially suited for use in MPC for IVHS. Note however that MPC is a modular approach so that in case a given prediction model does not perform well, it can easily be replaced by another prediction model.

C. Performance criteria and constraints

Possible performance criteria $J_{\text{perf}}(k)$ for MPC for IVHS are the total time spent in a traffic network, the total throughput, the total fuel consumption, safety, or a combination of these, all evaluated over the time period $[kT_{\text{ctrl}}, (k+N_{\text{p}})T_{\text{ctrl}})$.

Moreover, in order to prevent oscillations and frequent shifting in the control signals, one often adds a penalty on variations in the control signal u, which results in the total performance function

$$J_{\text{tot}}(k) = J_{\text{perf}}(k) + \alpha \sum_{j=0}^{N_{\text{c}}-1} \|u(k+j) - u(k+j-1)\|_2 \quad , \qquad (1)$$

at control step k, where $\alpha > 0$ is a weighting factor.

The MPC controller can also explicitly take into account operational constraints such as minimum separation between the platoons, minimum and maximum speeds, minimum headways, etc.

IV. Prediction models for IVHS

Now we describe simplified traffic models for vehicles and for platoons that can be used as (part of the) prediction model within the MPC-based roadside controller.

In this paper, we mainly deal with the longitudinal aspects of the driver tasks, which can be classified as free-flow, car-following, and stop-and-go behavior. In free-flow behavior, the vehicles can travel at their desired speed (corresponding to the speed limit, e.g., 120 km/h). As the traffic demand increases, the vehicles start to follow their predecessors at closer distances and at reduced speeds (50–80 km/h). Once the capacity of the highway is being utilized at its maximum, the vehicles move with stop-and-go movements (0–40 km/h).

A. Vehicle models

We use general kinematics motion equations to model the dynamics of the vehicles, which, after discretization leads to:

$$x_i(\ell+1) = x_i(\ell) + v_i(\ell)T_{\text{sim}} + 0.5a_i(\ell)T_{\text{sim}}^2 \qquad (2)$$

$$v_i(\ell+1) = v_i(\ell) + a_i(\ell)T_{\text{sim}} \qquad (3)$$

where ℓ is the simulation step counter, T_{sim} the simulation time step, $x_i(\ell)$ the longitudinal position of vehicle i at time $t = \ell T_{\text{sim}}$, $v_i(\ell)$ the speed of vehicle i at time $t = \ell T_{\text{sim}}$, and $a_i(\ell)$ the acceleration for vehicle i at time $t = \ell T_{\text{sim}}$. The acceleration used in (2)–(3) is calculated according to the current driving situation as will be explained below. In addition, the acceleration is limited between a maximum acceleration $a_{\text{acc,max}}$ and a maximum (in absolute value) comfortable deceleration $a_{\text{dec,max}}$.

B. Longitudinal models for human drivers

When there is no predecessor or when the time headway to the predecessor is larger than the critical time headway (e.g., 10 s), then the vehicle is said to be in free-flow mode. Once the vehicle travels with a smaller time headway than the critical time headway to its predecessor, then the vehicle is said to be in car-following mode.

1) Free-flow model: The acceleration for free-flow driving conditions is determined by the delayed difference between the current speed and the reference speed:

$$a_i(\ell) = K(v_{\text{ref},i}(\ell-\sigma) - v_i(\ell-\sigma)) \quad , \qquad (4)$$

where K is the proportional constant, $v_{\text{ref},i}$ is the reference speed, and σ is the reaction delay[1]. The reference speed can either be issued by roadside infrastructure or it can be driver's desired maximum speed.

2) Car-following model: As described in [7] there exist various types of car-following models such as stimulus response models [8], collision avoidance models [9], psychophysical models [10], and cellular automata models [11].

We will use a stimulus response model [8] to describe the behavior of human drivers as this model is most often used and also easy to implement. Stimulus response models are based on the hypothesis that each vehicle accelerates or decelerates as a function of the relative speed and distance between the vehicle and its predecessor. In particular, the Gazis-Herman-Rothery (GHR) model [12] states that after a reaction delay, the follower vehicle i accelerates or decelerates in proportion to the speed of the vehicle itself, to the relative speed with respect to its predecessor (vehicle $i+1$), and to the inverse of distance headway between them. The reference acceleration is thus

$$a_i(\ell) = C v_i^{\beta}(\ell) \frac{(v_{i+1}(\ell-d) - v_i(\ell-d))}{(x_{i+1}(\ell-d) - x_i(\ell-d))^{\gamma}} \quad , \qquad (5)$$

where C, β, and γ are the model parameters, and d is the driver delay[2].

C. Longitudinal models for intelligent vehicles

In our approach, intelligent vehicles will use adaptive cruise control (ACC) and intelligent speed adaptation (ISA) measures and are arranged in platoons. We now discuss how the accelerations for the platoon leaders and for the follower vehicles within a platoon are calculated.

[1] We assume here that the reaction time T_{react}, which typically has a value of 1–1.2 s, is an integer multiple of the simulation time step T_{sim}. So, $T_{\text{react}} = \sigma T_{\text{sim}}$ with σ an integer.

[2] Here we assume again that T_{delay}, which typically has a value of 1–1.2 s, is an integer multiple of T_{sim}. So, $T_{\text{delay}} = dT_{\text{sim}}$ with d an integer.

1) Platoon leader model: Platoon leaders have an enforced-ISA system and the calculation of their acceleration is based on a simple proportional controller:

$$a_i(\ell) = K_1(v_{\text{ISA}}(\ell) - v_i(\ell)) \ , \tag{6}$$

where K_1 is the proportional constant and v_{ISA} is the reference ISA speed provided by the roadside controller.

2) Follower vehicle model: The follower vehicles will use their on-board ACC system to maintain short intraplatoon distances. The ACC algorithm consists of a combined speed and distance controller:

$$\begin{aligned} a_i(\ell) = K_2(h_{\text{ref},i}(\ell) - (x_{i+1}(\ell) - x_i(\ell))) \\ + K_3(v_{i+1}(\ell) - v_i(\ell)) \ , \end{aligned} \tag{7}$$

where K_2 and K_3 are constants, and $h_{\text{ref},i}$ is the reference distance headway for vehicle i. The distance controller calculates the safe distance headway as follows:

$$h_{\text{ref},i}(\ell) = S_0 + v_i(\ell)T_{\text{head},i} + L_i \ , \tag{8}$$

where S_0 is the minimum safe distance that is to be maintained at zero speed, $T_{\text{head},i}$ is the time headway for vehicle i, and L_i is the length of vehicle i.

D. Platoon-based prediction model

On a more aggregate level, we can also consider a platoon of vehicles as a single entity without taking the detailed interactions among the individual vehicles within a platoon into account. So essentially we consider a platoon as one vehicle with a length that is a function of the speed of the platoon (due to the dependence of the intervehicle spacing managed by the ACC on the speed (cf. (8))), and of the number and lengths of the vehicles in the platoon. The dynamics equations for the speed and position of the platoon are the same as those of a platoon leader presented above. Consider platoon p and assume for the sake of simplicity that the vehicles in the platoon are numbered 1 (last vehicle), 2 (one but last vehicle), ..., n_p (platoon leader). The speed dependent length $L_{\text{platoon},p}(\ell)$ of platoon p is then given by

$$L_{\text{platoon},p} = (n_p - 1)(S_0 + S_1 v_{n_p}(\ell)) + \sum_{i=1}^{n_p} L_i \ , \tag{9}$$

where $S_0 + S_1 v_{n_p}(\ell)$ is the speed-dependent intervehicle spacing between the vehicles in the platoon, with S_1 a model constant, and v_{n_p} is the speed of the platoon (leader).

E. Merging at on-ramps

In order to model the merging behavior of platoons at on-ramps we could use a simplified model that operates at the platoon level. We consider each platoon at the on-ramp as one entity that will join the mainstream lane as soon as there is a sufficient large gap (including safety distances) available between the platoons on the mainstream lane and provided that the merging will not result in a collision in the next time steps. If both conditions are satisfied then the platoon joins the mainstream line (with a speed that is imposed by the roadside controller).

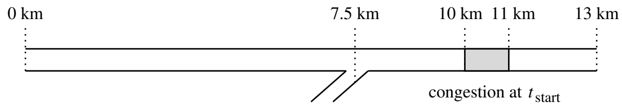

Fig. 3. Set-up of the case study.

For individual vehicles not controlled by the roadside controller we can use a similar model, i.e., the vehicle joins the mainstream line provided that there is a sufficiently large gap and that no collision is imminent; the vehicle's speed can then be taken equal to that of the immediate predecessor (if present) or equal to the ISA speed limit otherwise.

V. Case study

In this section, we present a simple case study in which the MPC control strategy described in Section III is used by the roadside controller layer. We consider dynamic speed limits and on-ramp metering as control measures.

A. Set-up

As a test-bed for illustrating the proposed IVHS-MPC approach we use a basic set-up consisting of a 13 km single-lane highway stretch with one mainstream origin, one on-ramp (located at position $x = 7.5$ km), and one destination (see Figure 3). We will compare three different situations:

- uncontrolled traffic (with human drivers),
- controlled traffic with human drivers and with autonomous ISA and conventional ramp metering as control measures,
- IV-based traffic control with platoons and with dynamic speeds and on-ramp release times for the platoons as control measures.

For the sake of simplicity all vehicles are assumed to be of the same length ($L_i = 4$ m). For the controlled situation with human drivers we assume that ISA limits the speed in a hard way and that human drivers cannot surpass the imposed speed limit. Similarly, we assume that the imposed ramp metering rate is adhered to. In the IV-based case with platoons we assume that all the vehicles are fully automated IVs equipped with advanced communication and detection technologies such as in-vehicle computers and sensors, and with on-board ACC and ISA controllers.

B. Scenario

We simulate a period of 15 min starting at time $t_{\text{start}} = 7$ h 20 min and ending at time $t_{\text{end}} = 7$ h 35 min. The demand of vehicles is taken to be constant during the simulation period, and equals 900 veh/h for the mainstream origin, and 350 veh/h for the on-ramp.

In the proposed scenario the initial state of the network is as follows. There is a congestion from position $x = 10$ km up to $x = 11$ km at time t_{start}. In the congested area there are 100 vehicles with speed 0 km/h; in the non-congested area there are 70 vehicles (uniformly distributed) with speed 120 km/h. Moreover, the on-ramp and mainstream origin queues are empty. After time t_{start}, the traffic flow in the congested area returns slowly to its regular value. As long as the congestion exists[3], the maximum outflow from the traffic jam is less when compared to free-flow traffic due to the capacity drop [13]. The value of this capacity drop in our case is around 7 % for human drivers (both in the controlled and the uncontrolled case) and 0 % for platoons (due to the full automation).

C. Models

In order to compare the results obtained for the given scenario using human driving (both without and with control) and using our platoon-based hierarchical approach, we have developed simulation models in Matlab for human driving and platoon driving. For the sake of simplicity and to avoid calibration, we have used the same models for both simulation and prediction purposes in this simulation study.

For the vehicle models we have used the models of Section IV. In particular, we have used (2)–(3) with the reference accelerations given by respectively (4)–(5) for uncontrolled human drivers, (4)–(5) with $v_{\mathrm{ref},i}(\ell)$ equal to the ISA speed limit for human drivers with ISA, and (6)–(8) for platoons of intelligent vehicles. If we express distances in m, times in s, speeds in m/s, accelerations in m/s^2, etc., the values of the various parameters in these models have the following values. For the car-following model (5) we have[4] $C = 1.55$, $\beta = 1.08$, and $\gamma = 1.65$ for acceleration, and $C = 2.55$, $\beta = -1.67$, and $\gamma = -0.89$ for deceleration. Furthermore, we have selected $\sigma = 1$, $d = 1$, $K = 0.01$, and $K_1 = 0.4$. For the follower vehicle model (7)–(8) we have $K_2 = 0.3$, $K_3 = 1$, $S_0 = 3$, and $T_{\mathrm{head}} = 1$ for all vehicles. For the platoon model (9) we have selected $S_1 = 1$. Moreover, $a_{\mathrm{acc,max}} = 5$ and $a_{\mathrm{dec,max}} = -5$ for all models.

The time step T_{sim} for the simulations is set to 1 s.

D. Control problem

The goal of our traffic controller is to improve the traffic performance. The objective that we consider is minimization of the total time spent (TTS) by all the vehicles in the network using dynamic speed limits and on-ramp metering as the control handles. The TTS for the entire simulation period can be expressed as

$$J_{\mathrm{TTS,sim}} = \sum_{\ell=1}^{N_{\mathrm{sim}}} \big(n_{\mathrm{veh}}(\ell) + q_{\mathrm{main}}(\ell) + q_{\mathrm{on}}(\ell)\big) T_{\mathrm{sim}} \quad , \qquad (10)$$

where $N_{\mathrm{sim}} = 900$ is the total number of simulation steps (of length $T_{\mathrm{sim}} = 1$ s) within the entire simulation period of 15 min, $n_{\mathrm{veh}}(\ell)$ is the number of vehicles that are present within the network at time $t = t_{\mathrm{start}} + \ell T_{\mathrm{sim}}$, $q_{\mathrm{main}}(\ell)$ is the number of vehicles in the queue at the mainstream origin at time $t = t_{\mathrm{start}} + \ell T_{\mathrm{sim}}$, and $q_{\mathrm{on}}(\ell)$ is the number of vehicles present in the on-ramp queue at time $t = t_{\mathrm{start}} + \ell T_{\mathrm{sim}}$.

[3]E.g., nearly 4 min after t_{end} for the uncontrolled case

[4]These values are inspired by the ones used in MITSIM [14].

The corresponding performance function $J_{\mathrm{perf}}(k)$ used in the MPC approach at control step k is then given by

$$J_{\mathrm{perf}}(k) = \sum_{\ell=kK+1}^{(k+N_{\mathrm{p}})K} \big(n_{\mathrm{veh}}(\ell) + q_{\mathrm{main}}(\ell) + q_{\mathrm{on}}(\ell)\big) T_{\mathrm{sim}} \quad ,$$

with[5] $K = \frac{T_{\mathrm{ctrl}}}{T_{\mathrm{sim}}}$. In the total MPC objective function we have also included a penalty term with $\alpha = 0.02$ (cf. (1)).

For the controlled human situation the applied control measures are ISA (with one speed limit for each section of 1 km length between position $x = 0$ km and position $x = 10$ km[6]) and on-ramp metering. So the control signal u for the MPC problem of control step k includes the ISA speed limits for the first 10 sections and the ramp metering rates (expressed as a number between 0 and 1) at control steps k up to $k + N_{\mathrm{c}} - 1$ (i.e., $11N_{\mathrm{c}}$ variables in total).

For the platoon-based approach the control signal u for the MPC problem of control step k includes speed limits for all platoons that are present in the network as well as the on-ramp release times for the platoons waiting at the on-ramp both for control steps k up to $k + N_{\mathrm{c}} - 1$. So if P_k is the number of platoons present in the network at control step k and that could enter the network between time $t = kT_{\mathrm{ctrl}}$ and time $t = (k + N_{\mathrm{p}})T_{\mathrm{ctrl}}$ and if Q_k is the number of platoons that could enter the network between $t = kT_{\mathrm{ctrl}}$ and $t = (k + N_{\mathrm{p}})T_{\mathrm{ctrl}}$, we have $P_k N_{\mathrm{c}} + Q_k$ variables in total.

As we focus on dynamic speed limits for each platoon and on on-ramp metering, the platoon size is not yet considered to be a control variable, but kept fixed at 10 for all platoons.

We consider a maximum speed of 120 km/h for both the human drivers and the platoon leaders. In the platoon-based approach the roadside controller has to take care of maintaining safe interplatoon distances. This condition is included as a constraint in the MPC optimization problem. In particular, the minimal safe distance between a platoon p_1 and its immediate predecessor platoon p_2 in the same lane is given by (cf. (8)): $S_{0,\mathrm{platoon}} + T_{\mathrm{head,platoon}}\, v_{\mathrm{platoon},p_1}$, where v_{platoon,p_1} is the speed of platoon p_1. For the case study we have selected $S_{0,\mathrm{platoon}} = 20$ m and $T_{\mathrm{head,platoon}} = 2$ s.

The control sampling time T_{ctrl} is set at 1 min. For the prediction horizon N_{p} we have taken a value that corresponds to 13 min, and for the control horizon N_{c} we have selected a value that corresponds to 2 min so as to limit the number of optimization variables.

In this case study we have opted to use multi-start pattern search [15] because our simulation experiments have shown that this optimization method provides a good trade-off between optimality and speed. In particular, we have used the `patternsearch` command incorporated in the Genetic Algorithm and Direct Search Toolbox of Matlab.

E. Results and analysis

For the scenario presented above, a closed-loop MPC simulation has been carried out. Table I lists the TTS for

[5]We select T_{ctrl} to be an integer multiple of T_{sim}. So K will be an integer.

[6]Note that considering speed limits in the remaining sections is not necessary in the proposed scenario as for these sections setting the speed limits equal to 120 km/h yields an optimal solution.

Case	TTS (veh.h)	Relative improvement
uncontrolled case	39.80	0 %
controlled (human drivers)	35.43	10.98 %
controlled (platoons)	29.39	26.16 %

TABLE I

RESULTS OF THE THREE APPROACHES. THE TTS IS THE TOTAL TIME SPENT BY ALL VEHICLES IN THE NETWORK DURING THE ENTIRE SIMULATION PERIOD (SEE (10)).

the three cases (i.e., uncontrolled, controlled with human drivers, and controlled with platoons) as well as the relative improvement compared to the uncontrolled case. In particular, we report $J_{\mathrm{TTS,sim}}$, the total time spent by all vehicles in the network during the entire simulation period of 15 min. Clearly, the IV-based traffic with platoons results in the best performance with an improvement of about 26 % with respect to the uncontrolled case.

The results can be explained as follows. In the uncontrolled case with human drivers, when there are no vehicles in front of the driver or if there is enough space between drivers, the drivers maintain their desired speed. But when a driver is confronted with a traffic jam, he has to decelerate in order to avoid a collision and he has to wait until the incident gets cleared. Moreover, there is no ramp metering action that can prevent or delay an extra flow of vehicles from entering the mainstream highway. All this results in a large time spent in the network for that vehicle, and thus also in a higher value of the TTS.

For the same scenario but with human drivers and ISA control, the MPC approach can predict the presence of the congestion and prevent it or diminish its negative impacts by slowing down vehicles (using speed limits) or delaying vehicles (via on-ramp metering) before they reach the congested area. For the platoon-based approach there is an additional performance improvement caused by the full automation, which allows to maintain small intervehicle distances (so that more cars are allowed to traverse the network more quickly) and which results in an almost 0 % capacity drop.

VI. CONCLUSIONS AND FUTURE RESEARCH

We have presented how model predictive control (MPC) can be used to determine optimal platoons speeds and optimal platoon release times at on-ramps in IVHS. The proposed approach has been illustrated using a case study based on simulations and with dynamic speed limits and on-ramp metering as control measures. The results of the case study highlight the potential benefits and improvements that can be obtained by using MPC for intelligent speed adaptation in IVHS.

Future research topics include: additional and more extensive case studies, inclusion of additional control measures (such as lane allocation, variable platoon sizes, etc.), explicit consideration of the other levels in the IVHS control hierarchy of [3], and extension to larger networks.

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