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Traffic Management for Automated Highway Systems using Model-Based Predictive Control

L.D. Baskar, B. De Schutter, and H. Hellendoorn

Abstract—**We present an integrated traffic management and control approach for Automated Highway Systems (AHS). The AHS consist of interacting roadside controllers and intelligent vehicles that 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. The proposed control approach is based on a hierarchical traffic control architecture for AHS, and it also takes the connection and transition between the non-automated part of the road network and the AHS into account. In particular, we combine dynamic speed limits and lane allocation for the platoons on the AHS highways with access control for the on-ramps using ramp metering, and we propose a model-based predictive control approach to determine optimal speed limits and lane allocations as well as optimal release times for the platoons at the on-ramps. In order to illustrate the potential of the proposed traffic control method, we apply it to a simple simulation example.**

Index Terms—**automated highway systems, traffic control, intelligent vehicles, intelligent vehicle highway systems, automated platooning.**

I. Introduction

On the short term one of the most promising approaches to reduce the frequency and 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. As a next step in this direction, advanced control methods and advanced communication and information technologies 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, such as Intelligent Vehicle Highway Systems (IVHS) [1], Intelligent Transportation Systems [2], Automated Highway Systems [3], or Cooperative Vehicle Infrastructure Systems [4].

In AHS every vehicle contains an automated 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 [5]. Moreover, compared to the situation with human drivers, the full automation present in AHS also has a positive effect on delays and reaction times. In practice, traffic congestion results in capacity drop [6], which causes the expected maximum outflow from the jammed region to be less than in the case of free-flow traffic. This is mainly due to the delay in reaction time and increased intervehicle distance when vehicles start to exit from a traffic jam. For human drivers the capacity drop is typically of the order of 2–7 % [7]. With fully automated vehicles the capacity drop can be reduced to almost 0 %, which results in an even more efficient use of the available infrastructure.

In this paper, we consider a variant of AHS in which the monitoring and control capabilities 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, lane closures, etc. The overall control framework we use is a hierarchical framework. We focus on the control layer that manages the different platoons in the fully automated AHS as well as at the access points to the AHS from the non-automated part of the traffic network. More specifically, we consider a model-based predictive control (MPC) approach to determine

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appropriate speed limits and lane allocations for the platoons within the AHS, and appropriate release times of vehicles or platoons that enter the AHS through on-ramps so as to optimize the performance of the traffic system. Possible performance measures in this context are throughput, travel times, fuel consumption, etc.

The paper is organized as follows. In Section II we propose the new hierarchical IV-based traffic control framework. Section III briefly describes the general principles of MPC. Next, we explain in Section IV how MPC can be adapted for traffic management and control in AHS. In Section V we apply the proposed approach to a case study based on simulations and we illustrate the potential effects of the proposed approach on the performance of an AHS. We want to mention that the case study is an illustration and primarily serves as an explanation for our control approach.

II. A Hierarchical Framework for IV-Based Traffic Management

We now briefly present the hierarchical control framework for AHS we have proposed in [8], [9], and which is closely related to the PATH framework [1], [5]. An Intelligent Vehicle (IV) system senses the environment around the vehicle using sensors (such as radar, laser) and strives to achieve more efficient vehicle operation either by assisting the driver (advisory/warning) or by taking complete control of the vehicle [10]. The framework [8], [9] 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. We consider various IV technologies that support both roadside traffic control measures and automated platoons of IVs including:

- Intelligent Speed Adaptation (ISA) influences the traffic flow by externally controlling the speed of the vehicles by limiting the maximum speed depending on the current traffic conditions [11], [12].
- Adaptive Cruise Control (ACC) extends conventional cruise control and is designed to automatically adjust the speed of the equipped vehicle to that of the preceding one [13], [14]. Cooperative ACC is a further enhancement of ACC that utilizes existing communication technologies (e.g., ad hoc wireless networks) to maintain a safe but small headway, and to ensure smooth driving [15].

The control architecture 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 Fig. 1. The layers of the framework can be characterized as follows:

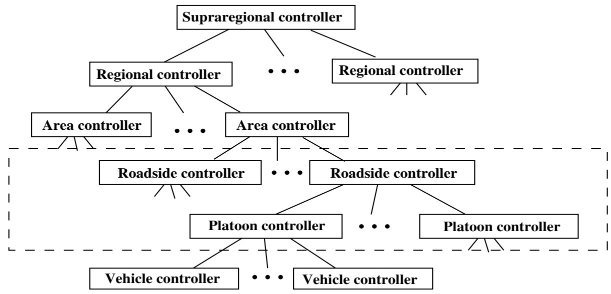

Figure 1. IV-based framework.

- *Higher-level controllers* (such as area, regional, and supraregional controllers) provide network-wide coordination of the lower-level and middle-level controllers as well as long-distance route assignment and route planning. E.g., the activities of a group of roadside controllers (see below) 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.
- *Roadside controllers* may control a part of a highway, an entire highway, or a collection of highways. The main tasks of the roadside controllers are to assign desired speeds and lanes for each platoon, safe distances to avoid collisions between platoons, and desired platoon sizes depending on the traffic conditions, to provide dynamic route guidance for the platoons (within the region controlled by the roadside controller), and to instruct for merges, splits, and lane changes of platoons.
- *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 concerned with actually executing the interplatoon maneuvers (e.g., merges, splits, lane changes) and with intraplatoon activities (e.g., maintaining safe intervehicle distances).
- *Vehicle controllers* present in each vehicle receive commands from the platoon controllers (e.g., setpoints or reference trajectories for speeds, headways, and paths) and they translate these commands into control signals for the vehicle actuators (e.g., throttle, braking, and steering actions).

Time scales involved

The time scales involved in our framework vary from milliseconds to hours as one traverses from the dynamics of the vehicle up to the roadside infrastructure levels. The time scale and update frequency typically ranges from milliseconds to seconds for vehicle controllers, from seconds to minutes for platoon controllers, from

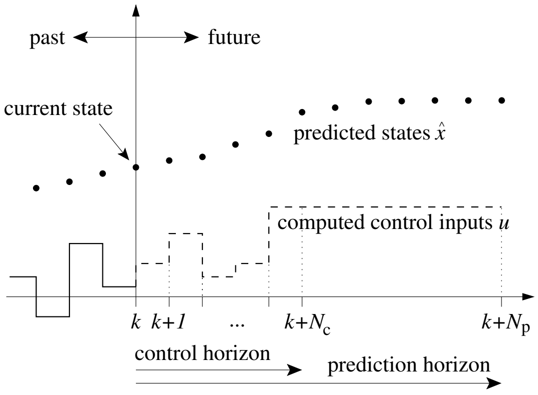

Figure 2. Schematic representation of MPC.

minutes to quarters of an hour for roadside controllers, and hours for area controllers.

In the remainder of the paper we will focus on the roadside controllers and on their interaction with the platoons and the platoon controllers. Note that the roadside controller considers each platoon in the highway network as a one single entity. 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.

We also consider the interface between the fully automated AHS 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 AHS control architecture will take over control of the vehicles and arrange them in platoons. To the authors' best knowledge, there are no strict rules available in the literature on how to form platoons and on how many vehicles to include in a platoon. There are a few articles that deal with vehicle sorting with respect to platoon sizes and platoon formation time, and with the design of platoon maneuver protocols [16], [17]. Once the platoons are formed, the roadside controllers of the AHS control structure then determine the release times of these platoons into the AHS network.

III. Model Predictive Control (MPC)

Model Predictive Control (MPC) is an on-line, sampling-based, discrete-time receding horizon control approach that uses (numerical) optimization and an explicit prediction model to determine the optimal values for the control measures over a given prediction period [18], [19]. One of the main advantages of MPC is that it can handle various hard constraints on the inputs and states of the system. In addition, MPC has a built-in feedback mechanism due to the use of a receding horizon approach, and it is easy to tune.

MPC works as follows (see Fig. 2). Let T_{ctrl} be the control time step, i.e., the time interval between two updates of the control signal settings. At each control step k (corresponding to the time instant $t = kT_{\mathrm{ctrl}}$), the roadside controller first measures or determines the current state $x(k)$ of the system. Next, the controller uses optimization in combination with a model of the system to determine the control sequence $u(k), \ldots, u(k+N_{\mathrm{p}}-1)$ that optimizes a given performance criterion $J_{\mathrm{perf}}(k)$ over a time interval $[kT_{\mathrm{ctrl}}, (k+N_{\mathrm{p}})T_{\mathrm{ctrl}}]$ subject to the operational constraints. Here, N_{p} denotes the prediction horizon. In order to reduce the computational complexity, 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} ($< N_{\mathrm{p}}$) 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/optimization procedure over the shifted horizon is repeated using new system measurements. This receding horizon approach introduces feedback, which allows to reduce the effects of possible disturbances and mismatch errors.

IV. MPC for AHS

In this section we explain in detail how MPC can be used for traffic management and control of AHS. We focus on the roadside controller, and in particular on how MPC can be applied for speed control, lane allocation, and on-ramp control in AHS.

A. States and control inputs

Recall that at every control step the MPC controller measures or estimates the current state of the traffic network. Since the roadside controllers work with platoons as basic entities, in our case the state of the system includes the positions, lanes, 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 at the on-ramps of the AHS network.

The control signal consists of the speed limits for the platoon leaders, lane allocations for the platoons, on-ramp release times, etc. Note that in principle the platoon size could also be a decision variable. However, to reduce the computational complexity, we may update the platoon sizes at a slower rate than the other control variables. Alternatively, we could assume that the platoon sizes can only change at the boundaries of the region controlled by a roadside controller and are thus fixed for platoons already in the network.

So, the control signal u for the MPC problem of control step k includes speed limits and lane allocations for all platoons that are or will be present in the network during the control horizon period as well as the on-ramp release times for the platoons at the on-ramp during the control horizon period.

To keep the number of optimization variables fixed during the optimization process and to take the future demand of platoons into account, we can use autonomous control for vehicles entering between $t = (k + N_{\rm c})T_{\rm ctrl}$ and $t = (k+N_{\rm p})T_{\rm ctrl}$. By autonomous control, we mean that the platoons on the highways would be assigned with the speed of its immediate predecessor platoon. If no predecessor platoon exists then the free-flow speed will be assigned to the uncontrolled autonomous platoon. Moreover, each autonomous platoon will be assigned the same lane in which it originated, unless it is forced to perform a lane change due to e.g., any incident blockages. The autonomous platoons from on-ramps are allowed to enter the highway once the highway–on-ramp merging location can accommodate the entire platoon.

B. Performance criterion and constraints

Possible performance criteria $J_{\rm perf}(k)$ for MPC for AHS 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 $[kT_{\rm ctrl}, (k + N_{\rm p})T_{\rm ctrl}]$. 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

$$J_{\rm tot}(k) = J_{\rm perf}(k) + \alpha \sum_{j=0}^{N_{\rm c}-1} \|u(k+j) - u(k+j-1)\|_2^2, \tag{1}$$

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

MPC can also explicitly take into account operational constraints such as minimum separation between the platoons, minimum and maximum speeds, minimum headways, or in case a vehicle or a platoon has to take an exit, a constraint that it should have moved into the rightmost lane X km before the exit, etc.

C. Optimization methods

Solving the MPC optimization problem (i.e., computing the optimal control actions) is the most demanding operation in the MPC approach. In our case the MPC approach gives rise to nonlinear non-convex optimization problems that have to be solved on-line. Moreover, in general there will be continuous variables (dynamic speed limits, metering rates, release times, etc.) as well as integer variables (lane allocations, platoon sizes, etc.). Hence, a proper choice of optimization techniques that suit the nature of the problem has to be made. In our case global or multi-start local optimization methods are required such as multi-start sequential quadratic programming [20, Chapter 5] or multi-start pattern search [21] in the continuous case, or branch-and-bound algorithms [22], genetic algorithms [23], or simulated annealing [24] in the mixed integer case.

D. Prediction models for AHS

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 used.

Remark 1: It is important to note that the proposed MPC approach is *generic* and *modular*, so that in case a given prediction model does not perform well, it can easily be replaced by another, more complex prediction model. $\diamond$

Since in the case study of Section V we will compare the platoon-based approach with the case of human drivers, we will discuss models both for human drivers and for intelligent vehicles and platoons.

1) Vehicle models: We use general kinematic equations to describe the behavior of the vehicles, which, after discretization leads to:

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

$$v_i(\ell+1) = v_i(\ell) + a_i(\ell)T_{\rm sim} \tag{3}$$

where ℓ is the simulation step counter[1], $T_{\rm sim}$ the simulation time step, $x_i(\ell)$ the longitudinal position of the rear of vehicle i at time $t = \ell T_{\rm sim}$, $v_i(\ell)$ the speed of vehicle i at time $t = \ell T_{\rm sim}$, and $a_i(\ell)$ the acceleration for vehicle i at time $t = \ell T_{\rm sim}$. 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 $a_{\rm acc,max}$ and a maximum (in absolute value) comfortable deceleration $a_{\rm dec,max}$. So

$$a_i(\ell) = {\rm sat}(a_{{\rm target},i}(\ell), a_{\rm dec,max}, a_{\rm acc,max}) \tag{4}$$

[1]In general, $T_{\rm sim} \neq T_{\rm ctrl}$ and that is why we use different counters ℓ and k for the simulation step and the control step respectively.

where sat is the saturation function[2] and $a_{\text{target},i}(\ell)$ is the reference acceleration computed via the formulas given in the next subsections.

We will also use the concept of time and space headway, which are defined as follows. The distance between the front of the following vehicle and the rear of the vehicle in front is called the following distance Δ_i. The time headway h_i of a vehicle is defined as the time difference between the passing of the rear ends of the vehicle's predecessor and the vehicle itself at a certain location. When the speeds of the vehicles are considered to be constant, then the time headway is the amount of time necessary for vehicle i to reach the current position of vehicle $i+1$. The distance headway of a vehicle s_i is defined as the distance between the rear of the vehicle and the rear of its predecessor vehicle at a specific instant of time. The distance headway s_i is thus equal to the sum of the vehicle length L_i and its following distance Δ_i.

2) Longitudinal models for human drivers: We distinguish between free-flow and car-following behavior:

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

$$a_{\text{target},i}(\ell) = K(v_{\text{ref},i}(\ell-\sigma) - v_i(\ell-\sigma)) \quad , \tag{5}$$

  where K is a model parameter, $v_{\text{ref},i}$ is the reference speed, and σ is the reaction delay. The reference speed $v_{\text{ref},i}$ can either be issued by the roadside controller or it can be the driver's desired speed or the legal maximum speed for the road the vehicle is currently on. In connection with the reaction delay σ we assume that the corresponding 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}. As a result, $\sigma = \dfrac{T_{\text{react}}}{T_{\text{sim}}}$ is an integer.
- *Car-following model*: As described in [25] there exist various types of car-following models such as stimulus response models [26], collision avoidance models [27], psychophysical models [28], and cellular automata models [29].

  As an example, we use a stimulus response model to describe the behavior of human drivers. We have selected this model for our research mainly due to the simple formulation used by the model to describe the car-following behavior (see however also Remark 1). 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 [30] 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 acceleration is thus given by

$$a_{\text{target},i}(\ell) = C v_i^{\beta}(\ell) \frac{(v_{i+1}(\ell-d) - v_i(\ell-d))}{(x_{i+1}(\ell-d) - x_i(\ell-d))^{\gamma}} \quad , \tag{6}$$

  where C, β, and γ are the model parameters (possibly with different values depending on whether the vehicle is accelerating or decelerating), and d is the driver delay. Here we assume again that the driver delay time T_{delay}, which typically has a value of 1–1.2 s, is an integer multiple of T_{sim}. So, $d = \dfrac{T_{\text{delay}}}{T_{\text{sim}}}$ is an integer.

3) Longitudinal models for platoons in AHS: In our approach, the intelligent vehicles within the platoons use cooperative adaptive cruise control (CACC) and intelligent speed adaptation (ISA) and are arranged in platoons [31]–[33]. We now discuss how the accelerations for the platoon leaders and for the follower vehicles within a platoon are calculated:

- *Platoon leader model*: Platoon leaders have an enforced-ISA system and the calculation of the acceleration for the platoon leader is based on a simple proportional controller:

$$a_i(\ell) = K_1(v_{\text{ISA}}(\ell) - v_i(\ell)) \quad , \tag{7}$$

  where K_1 is the proportional constant and v_{ISA} is the reference ISA speed provided by the roadside controller.
- *Follower vehicle model*: The follower vehicles in a platoon will use their on-board CACC system to maintain short intraplatoon distances [15]. The CACC algorithm consists of a combined speed and distance controller:

$$\begin{aligned} a_i(\ell) = {} & K_2(d_{\text{ref},i}(\ell) - (x_{i+1}(\ell) - x_i(\ell))) \\ & + K_3(v_{\text{platoonleader}}(\ell) - v_i(\ell))) \quad , \end{aligned} \tag{8}$$

  where K_2 and K_3 are constants, and $d_{\text{ref},i}$ is the reference distance headway for vehicle i. The distance controller calculates the safe distance headway [26] as follows:

$$d_{\text{ref},i}(\ell) = S_0 + v_i(\ell) T_{\text{head},i} \quad , \tag{9}$$

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

[2]The saturation function sat is defined as follows: $\text{sat}(x, U, L) = x$ if $L < x < U$, $= U$ if $x \geq U$, and $= L$ if $x \leq L$.

4) Platoon-based prediction model: At 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 CACC on the speed (cf. (9)), 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. Now 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), $\ldots$, n_p (platoon leader). The speed dependent length $L_{\text{platoon},p}(\ell)$ of platoon p is then given by

$$L_{\text{platoon},p} = (n_p - 1)S_0 + \sum_{i=1}^{n_p-1} T_{\text{head},i} v_{n_p}(\ell) + \sum_{i=1}^{n_p} L_i \ , \tag{10}$$

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

5) Merging and lane changing: In order to model the merging and lane changing behavior of vehicles, we could — in the interest of simulation speed and efficiency — use the following simplified models.

a) Merging at on-ramps and lane changing for human drivers: For individual human-driven vehicles (cf. the case study of Section V below) we assume that a vehicle on an on-ramp can join the mainstream lane provided that there is a sufficient large gap and that no collision is imminent. The vehicle then joins the mainstream line with a speed that is equal to that of the immediate predecessor if present or equal to the (ISA or legal) speed limit otherwise.

Lane changes can be modeled similarly: if there is a slower vehicle ahead and if the speed of the vehicles in an adjacent lane is higher than that of the vehicle's predecessor in the current lane, the vehicle can join the other lane provided that there is a sufficient large gap and that no collision is imminent. In this case the vehicle's speed should not be modified.

b) Merging at on-ramps and lane changing for platoons: In order to model the merging behavior of platoons at on-ramps and the lane changing behavior of platoons, we could use a similar simplified model that operates at the platoon level.

We consider each platoon at an 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).

Likewise, if a lane change is imposed on a platoon by the roadside controller, we assume that the platoon moves to the assigned lane as one entity. Note that in this case the roadside controller is responsible for taking care that there is a sufficiently large gap (including safety distances) available between the platoons on the other lane and that the lane change will not result in a collision in the next time steps.

V. Case study

Now we present a simple case study in which the MPC control strategy for the roadside controller layer that has been described in Section III is applied. We want to reiterate that the case study is an illustration and primarily serves as an explanation for our approach.

A. Set-up

To illustrate the proposed MPC approach for the roadside controller we use a basic set-up consisting of a 7 km two-lane highway stretch with one mainstream origin, two on-ramps (located at position $x = 2000$ m and $x = 4000$ m), and one destination (see Fig. 3). We compare three different situations:

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

In both controlled case, MPC is used. For the sake of simplicity all vehicles are assumed to be of the same length ($L_i = 4$ m for i=1, 2, $\ldots$, n).

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.

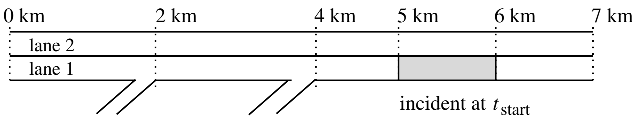

Figure 3. Set-up of the case study.

B. Scenario

We simulate a period starting at t_{start} = 7:00 A.M and ending at t_{end} = 7:09 A.M. The demand of vehicles is taken to be constant during the simulation period, and equals 1365 veh/h/lane (lane 1) and 1512 veh/h/lane (lane 2) for the mainstream origin and 404 veh/h (on-ramp 1) and 422 veh/h (on-ramp 2) for the on-ramps.

For the proposed scenario the initial state of the network is as follows. We assume that before time t_{start} an incident has occurred at position $x = 5$ km in lane 1, resulting in a blockage in lane 1 from position $x = 5$ km up to position $x = 7$ km at time t_{start}. This incident blockage will serve as the main bottleneck in our set-up.

In the upstream sections 3 and 4 of lane 2 (i.e., from position $x = 2$ km up to $x = 4$ km) the initial density is 50 veh/km/lane, and in the other sections there are no vehicles. Similarly, in the upstream section 4 of lane 1, the initial density is 25 veh/km/lane. Moreover, at time t_{start} the on-ramp and mainstream origin queues are empty. The incident situation continues for the entire simulation period $[t_{\text{start}}, t_{\text{end}}]$. During this interval, there is no outflow from the incident on the right-most lane (marked as lane 1 in Figure 3).

The demand profile considered for this particular lay-out is as follows: The demand profiles are linear and at time t_{start} start at 480 veh/h for lane 1 of the mainstream origin, at 660 veh/h for lane 2 of the mainstream origin, at 780 veh/h for on-ramp 1, and at 660 veh/h for on-ramp 2. The final demand at t_{end} is 1020 veh/h for lane 1, 1200 veh/h for lane 2, 580 veh/h and 530 veh/h for on-ramps 1 and 2 respectively. The highway has a capacity of 1600 veh/h/lane.

C. Models

In order to compare the simulation 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-D. In particular, we have used (2)–(3) with the accelerations given by respectively (5)–(6) (with $v_{\text{ref},i}(\ell)$ equal to the legal speed limit of 120 km/h) for uncontrolled human drivers, (5)–(6) (with $v_{\text{ref},i}(\ell)$ equal to the ISA speed limit) for human drivers with ISA, and (7)–(9) for platoons of intelligent vehicles. The headway used for manual car following is 1 s. If we express distances in m, times in s, speeds in m/s, accelerations in m/s^2, etc., then the various parameters in these models have the following values (inspired by the MITSIM model [34]): For the car-following model (6) we have $C = 1.55$, $\beta = 1.08$, and $\gamma = 1.65$ for deceleration, and $C = 2.55$, $\beta = -1.67$, and $\gamma = -0.89$ for acceleration. Furthermore, we have selected $d = 1$, $\sigma = 1$, $K = 0.01$, and $K_1 = 0.4$. For the follower vehicle model of the AHS approach (8)–(9) we have $K_2 = 0.6$, $K_3 = 1.2$, $K_4 = 1$, $S_0 = 3$, and $T_{\text{head}} = 0.5\,s$ for all vehicles. For the platoon model (10) we have selected $S_1 = 0.5$. Moreover, $a_{\text{acc,max}} = 3$ and $a_{\text{dec,max}} = -3$ for all models.

If there is a congestion in a segment of the highway, then the maximum outflow from this congested segment will become less when compared to free-flow traffic due to the capacity drop. The value of the capacity drop due to congestion in our case is around 7 % for human drivers (both in the controlled and the uncontrolled case) and almost 0 % for platoons (due to the full automation). For human drivers the capacity drop is included by setting the reaction delay d in the car-following model (6) equal to $d = 4$ for the first vehicle that leaves the situation, and by reducing this reaction delay every simulation step with 1, until it gets back to the regular value of $d = 1$. The threshold speeds for determining whether or not a given vehicle is in a congested or uncongested situation are 30 km/h and 50 km/h respectively (in between the previous congestion state is preserved; so the capacity drop model contains hysteresis). The time step T_{sim} for the simulations is set to 1 s.

D. Control problem

Objective function: The objective that we consider is minimization of the total time spent (TTS) by all the vehicles in the network using dynamic speed limits, lane allocations (for the platoons), and on-ramp metering as the control handles. The TTS for the entire simulation period can be expressed as

$$J_{\text{TTS,sim}} = \sum_{\ell=0}^{N_{\text{sim}}} \big(n_{\text{veh}}(\ell) + q_{\text{main}}(\ell) + q_{\text{on}}(\ell)\big) T_{\text{sim}} \quad , \tag{11}$$

where N_{sim} = 540 is the total number of simulation steps (of length T_{sim} = 1 s) within the entire simulation period, $n_{\text{veh}}(\ell)$ is the number of vehicles that are present within the network at time $t = \ell T_{\rm sim}$, $q_{\rm main}(\ell)$ is the number of vehicles in the queue at the mainstream origin at time $t = \ell T_{\rm sim}$, and $q_{\rm on}(\ell)$ is the number of vehicles present in the on-ramp queues at time $t = \ell T_{\rm sim}$.

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

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

with $M = \dfrac{T_{\rm ctrl}}{T_{\rm sim}}$ (note that as we will select the control time step $T_{\rm ctrl}$ to be an integer multiple of the simulation time step $T_{\rm sim}$, M will be an integer). In the total MPC objective function we also include a penalty term with $\alpha = 0.01$ (cf. Section IV-B).

Control inputs: For the controlled human situation, the control signal u for the MPC problem of control step k includes the ISA speed limits for the first 5 sections and the ramp metering rates for two on-ramps (expressed as a number between 0 and 1) at control steps k up to $k + N_{\rm c} - 1$, i.e., we have $7N_{\rm c}$ variables in total.[3]

For the platoon-based approach, we focus on dynamic speed limits and lane allocations for each platoon and on on-ramp metering. Although the platoon size can be considered to be a control variable, we have kept the platoon size fixed at 25[4]. The choice for this platoon size involved a trade-off between the requirements for practical implementation (which require relatively small platoon sizes) and the need for reducing the number of variables to be optimized by the roadside traffic controller (which requires relatively large platoon sizes).

Constraints: 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 the front end of a platoon p_1 and the rear end of its immediate predecessor platoon p_2 in the same lane is given by:

$$S_{0,\rm platoon} + T_{\rm head,platoon}\, v_{{\rm platoon},p_1}(\ell) \ ,$$

where $v_{{\rm platoon},p_1}$ is the speed of platoon p_1. For the case study we have selected $S_{0,\rm platoon} = 20\,$m and $T_{\rm head,platoon} = 1.2\,$s. Moreover, we consider a maximum speed of 120 km/h for both the human drivers and the platoon leaders.

[3]Considering speed limits in the remaining sections is not necessary in the given scenario as for these sections setting the speed limits equal to the legal speed limit of 120 km/h yields an optimal solution.

[4]This platoon length was set after considering the traffic demand for the whole simulation period, the traffic demand and control inputs that the MPC controller can handle within the specified $N_{\rm p}$ steps, and the size of the network itself.

Table I

RESULTS FOR THE THREE APPROACHES

Case	TTS (veh.h)	Relative improvement
uncontrolled case	27.44	0 %
controlled (human drivers)	24.72	9.91 %
controlled (platoon-based)	20.67	24.67 %

Horizons: The control time step $T_{\rm ctrl}$ is set at 1 min. The prediction horizon $N_{\rm p}$ is assumed to be the average time required for a vehicle to travel the entire network using the average speed. So for our case study we have taken a value that corresponds to 7 min ($N_{\rm p}$ = 7 km/60 km/h = 0.1 h = 7 min). For the control horizon $N_{\rm c}$ we have selected a value that corresponds to 3 min so as to limit the number of optimization variables.

Optimization algorithms: As we consider dynamic speed limits, on-ramp metering, and lane allocation as control measures there will be both continuous and integer variables in the MPC optimization problem. For the optimization we have used the pattern search method [21] implemented through `patternsearch` command incorporated in the Genetic Algorithm and Direct Search Toolbox of Matlab for the continuous optimization problems (i.e., the determination of the speeds and on-ramp metering rates for the controlled human case) and a bilevel optimization approach based on binary optimization and pattern search for the mixed integer optimization problems (i.e., the determination of the speeds, on-ramp release times, and lane allocation for the platoon case). We have opted to use these particular optimization algorithms because our simulation experiments have shown that they provide a good trade-off between optimality and speed. Both methods have been executed multiple times with different initial starting points so as to get a good approximation of the optimal solution. In particular, we have used 30 multiple initial points.

E. Results and analysis

For the scenario presented above, closed-loop MPC simulations have been carried out. The results of the simulations are reported in Table I. In particular, we indicate the total time spent by all vehicles in the network during the entire simulation period.

We will analyze the scenario for the reference case (uncontrolled case) as follows. The total capacity of the considered network highway equals 3200 veh/h (2 lanes × 1600 veh/h). In the actual simulation, the total demand equals 3703 veh/h (1365 veh/h+1512 veh/h+404 veh/h+422 veh/h), which is higher than the total capacity.

In the uncontrolled case, the congestion will mainly occur on the mainstream, as the vehicles from on-ramps will always try to enter the mainstream. The capacity available for the mainstream demands will be 3200-422 = 2778 veh/h (allowed capacity - demand on on-ramp 2), which is less than for the original demand (3281 veh/h, i.e., the demand from the mainstream origin and from on-ramp 1). This exceeding demand situation, when not controlled properly, will lead to traffic jams.

The considered set-up and scenario can be analyzed in three categories as follows: segments upstream the bottleneck, the bottleneck segment, and segments downstream the bottleneck. The segments far upstream the bottleneck i.e., segments from 1 to 4 allow vehicles to travel at their free-flow speed. However, segment 3 may get congested if the demand from on-ramp 1 exceeds the allowed capacity. Due to the constant, high demand from on-ramp 2 and from the mainstream origin, and due to the bottleneck caused by the incident, congestion is expected to occur on segment 5. In the bottleneck segment 6, the available capacity can be utilized fully by the vehicles, but at the price of low mean speeds. The outflow capacity from segment 6 cannot reach the maximum flow, as vehicles cannot travel fastly through the bottleneck.

Fig. 4 shows the simulation result for the uncontrolled case. The traffic flow direction is from the bottom to the top, and since all segments have the same length, the y axis should be interpreted as the distance traveled by the vehicles. During the entire simulation for the uncontrolled case, the speed limits for all the segments are set to 120 km/h. The first plot in Fig. 4 shows the mean speeds at the segments. Light colors represent high mean speeds. The dark area starting at the 5th segment after 1 min indicates low speeds; the reason for these decreased speeds (i.e., increased densities) can be interpreted as follows. When a driver is confronted with an incident on segment 6 on the same lane (lane 1), he starts to decelerate in order to avoid a collision. In case there is no space in lane 2 or in case the speed on lane 2 is almost the same as on lane 1, the driver waits and stays on lane 1 until the incident eventually gets cleared. However, once there is a possibility to perform a safe lane change maneuver, the driver moves to lane 2. In the uncontrolled case there is no ramp metering action that can prevent or delay an extra flow of vehicles from entering the mainstream highway. However, the increasing density in lane 2 due to the effects of the incident in lane 1 causes congestion, which in its turn leads to a capacity drop for vehicles leaving the traffic jam. Next, the flow plot also shows the traffic jam, which is visible as the dark area in segment 5, indicating a lower flow. Once the traffic congestion sets in, both the mainstream vehicles and the on-ramp vehicles drive on and have to wait in a queue until the traffic jam dissolves. All this results in a large time spent in the network for the vehicles, and thus also in a higher value of the TTS for the entire simulation period.

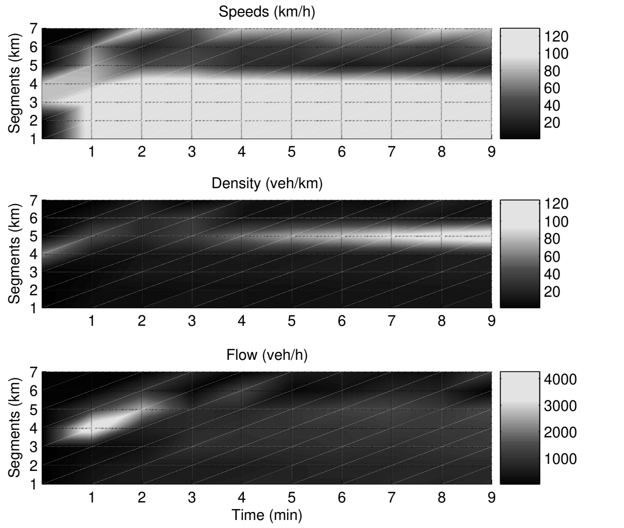

Figure 4. Simulations for the uncontrolled case with human drivers.

In the controlled case with humans, the segments where the speed limits can influence the traffic flow are segments 1 to 5. The speed limits become active and reduce the inflow from the mainstream, and ramp metering gradually switches on and keeps the total outflow high as shown in Fig. 5. For this case, the MPC approach can predict the presence of an incident and prevent it or diminish its negative impact by slowing down vehicles (using speed limits) or delaying vehicles (via on-ramp metering) before they reach the incident. In Fig. 5, we can see that the speed limit control in segments 4 and 5 delays the vehicles from reaching the bottleneck area as fast as possible (since the congestion will then be dissolved or at least less severe by the time the vehicles reach the congested area) and provides entry space for the on-ramp vehicles. This controlled approach with human drivers, ISA control, and ramp metering yields an improvement in TTS over the uncontrolled case of about 10 % (cf. Table I).

The result for platoon-based controlled case are shown in Fig. 6. Averaging effects in combination with the facts that the number of platoons in the traffic network is much smaller than the number of vehicles and that a given platoon may once in a while be present in two consecutive segments at the same time might explain the oscillation effect shown in the speed plot of Fig. 6. From the speed plot in Fig. 6, we can see that the platoons are allowed to travel at higher speeds through the segments.

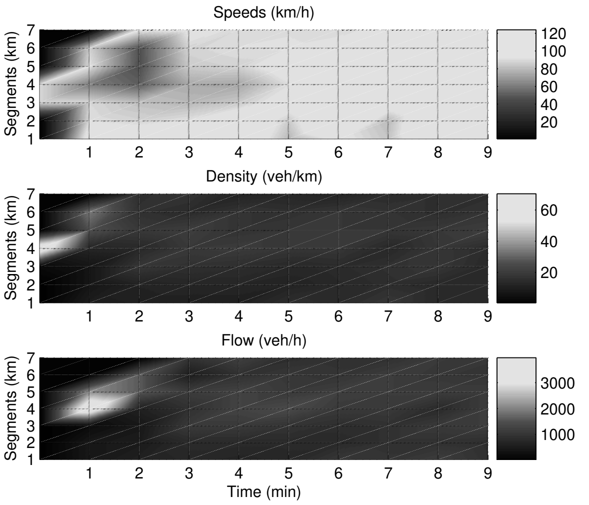

Figure 5. Simulations for the controlled case with human drivers.

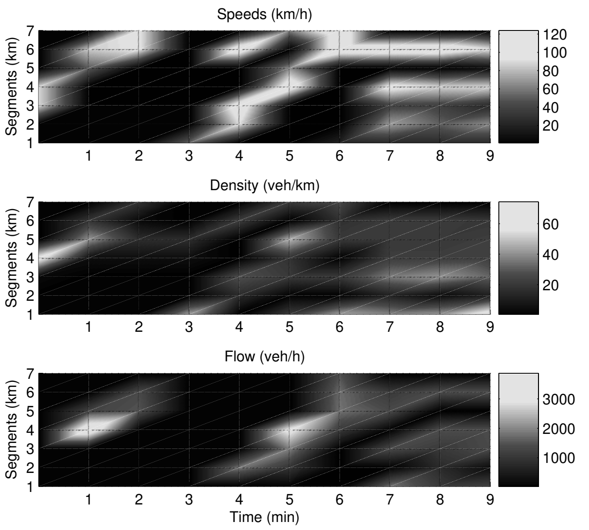

Figure 6. Simulations for the platoon-based controlled case.

The main idea behind speed limit control and on-ramp release time control for platoons is the same as for human controlled approach. Moreover, the full automation for AHS allows to maintain small intervehicle distances (so that more cars are allowed to traverse the network more quickly), even in the case of possible congestion in segment 5 (due to the incident and the demand at on-ramp 2) and it results in an almost 0 % capacity drop. The additional performance improvement obtained by our approach is caused by the optimal lane allocation and the full automation in addition to speed limits and ramp metering. Lane allocation control also helps to better react to the incident and to allow for lane changes for platoons that would otherwise be blocked in front of the congested region. IV-based traffic with platoons results in the best performance with an improvement of about 25 % with respect to the uncontrolled case and of about 16 % with respect to the controlled human case.

VI. Conclusions and Future Research

We have presented how model predictive control (MPC) can be used to determine optimal platoons speeds, lane allocations, platoon sizes, platoon release times at on-ramps, etc. in Automated Highway Systems (AHS). The proposed approach has been illustrated using a case study with dynamic speed limits, lane allocation, 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 AHS.

Future research topics include: more extensive case studies and comparisons, inclusion of additional control measures, development of efficient algorithms, extension to larger networks, assessment of scalability of the control approach, and further working out the presorting and access control mechanism.

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