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Traffic Management for Intelligent Vehicle Highway Systems using Model-Based Predictive Control

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Abstract.
In this paper we present an integrated traffic management and control approach for Intelligent Vehicle Highway Systems (IVHS). These IVHS 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 management and control architecture for IVHS, and it also takes the connection and transition between the non-automated part of the road network and the IVHS into account. In particular, we combine dynamic speed limits and lane allocation for the platoons on the IVHS 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 in which the aim is to minimize the total time all vehicles spend in the network by optimally assigning dynamic speed limits, lane allocations, and on-ramp release times to the platoons. For the case study the platoon-based approach results in a performance improvement of about 9 % compared to the situation with controlled human drivers.

1 INTRODUCTION

There are many ways to reduce the frequency and impact of traffic jams (such as building new roads, introducing road pricing, stimulating modal shift, promoting public transportation, etc.). On the short term one of the most promising approaches 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 the reminder of this paper we will use IVHS as a generic word to indicate (a mixture of) these systems.

In IVHS 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 IVHS 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 traffic 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 %. 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 IVHS 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 the hierarchical framework that we have presented in (*7*). In the current paper, we focus on the control layer that manages the different platoons in the IVHS as well as on the access to the IVHS from the non-automated part of the traffic network. More specifically, we will consider a model-based predictive control approach called MPC (Model Predictive Control) to determine appropriate speed limits and lane allocations 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 2 we recapitulate the hierarchical IV-based traffic control framework of (*7*). Section 3 describes the general principles of MPC. Next, we explain in Section 4 how MPC can be adapted for traffic management and control in IVHS. In Section 5 we apply the proposed approach to a case study based on simulations and we illustrate the potential effects of the proposed approach on the traffic flow performance of an IVHS. Section 6 concludes the paper.

2 A HIERARCHICAL FRAMEWORK FOR IV-BASED TRAFFIC MANAGEMENT

First we briefly present the hierarchical control framework for IVHS we have proposed in (*7*) and which is closely related to the PATH framework (*8*). The framework of (*7*) distributes the intelligence between

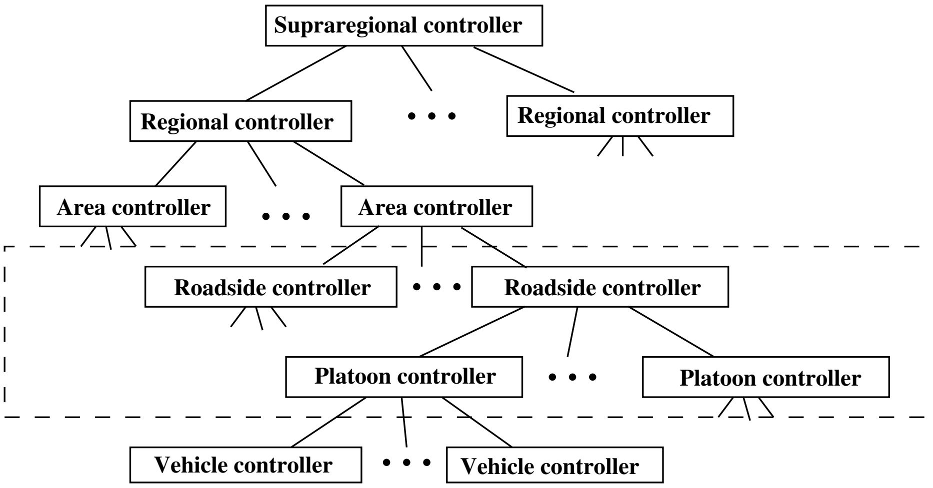


FIGURE 1 IV-based framework of (7). The focus of this paper is indicated by the dashed box.

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 (7) 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:

- *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 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.

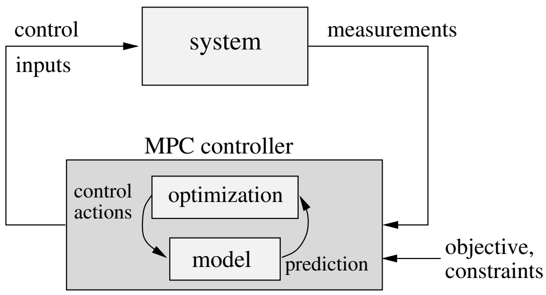
- *Roadside controllers* use IV-based control measures to improve the traffic flow. A roadside controller may control a part of a highway, an entire highway, or a collection of highways. The main tasks of the roadside controllers are to assign desired speeds and lanes for each platoon, safe distances to avoid collisions between platoons, 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 mainly concerned with actually executing the interplatoon maneuvers (e.g., merges, splits, and lane changes) and with intraplatoon activities (e.g., maintaining safe intervehicle distances).

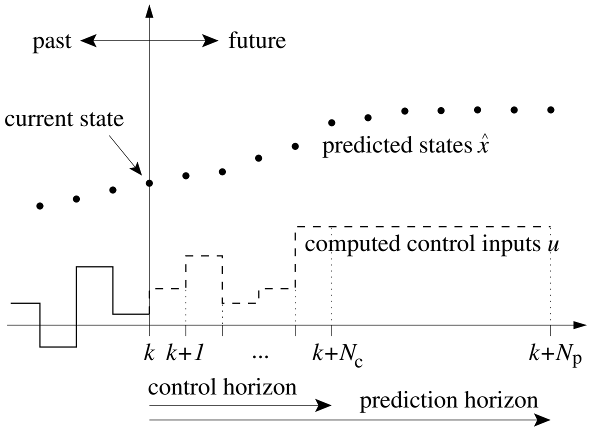
- *Vehicle controllers* present in each vehicle receive commands from the platoon controllers (e.g., set-points or reference trajectories for speeds, headways, and paths) and they translate these commands into control signals for the vehicle actuators (e.g., throttle, braking, and steering actions).

For a more extensive description of the framework and its main advantages and extensions with respect to the state of the art, the interested reader is referred to (7).

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



(a) The MPC control loop.



(b) Prediction and control horizon in MPC.

FIGURE 2 Schematic representation of MPC.

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.

In this paper 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. The roadside controllers of the IVHS control structure then determine the release times of these platoons into the IVHS network.

3 MODEL PREDICTIVE CONTROL (MPC)

In this section we briefly present the general principles of Model Predictive Control (MPC) (*9*) (see Figure 2).

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. 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. 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 an optimization algorithm 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 and optimization procedure over the shifted horizon are repeated using new system measurements. This receding horizon approach introduces a feedback mechanism, which allows to reduce the effects of possible disturbances and mismatch errors.

4 MPC FOR IVHS

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

4.1 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 IVHS network.

The control signal consists of the speed limits for the platoon leaders, lane allocations for the platoons, on-ramp release times, etc. All these control inputs will be updated at every control step. Note that in principle the platoon size (and the resulting split or merge decisions for platoons) could also be a decision variable. However, to reduce the computational complexity, we may either 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.

4.2 Performance Criteria and Constraints

Possible performance criteria $J_\mathrm{perf}(k)$ 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 $[kT_\mathrm{ctrl}, (k+N_\mathrm{p})T_\mathrm{ctrl})$.

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

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

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.

4.3 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 nonconvex 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 allocation, platoon size, 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 (*10*) or multi-start pattern search (*11*) in case there are only continuous variables, or branch-and-bound algorithms (*12*), genetic algorithms (*13*), or simulated annealing (*14*) in the mixed integer case.

4.4 Prediction Models for IVHS

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.

In this section we describe some (simplified) traffic models that could be used as (part of the) prediction model within the MPC-based roadside controller. Note however 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.

Since in the case study of Section 5 we will compare the platoon-based approach with human drivers, we will discuss models both for human drivers and for intelligent vehicles and platoons.

4.4.1 Vehicle Models

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

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

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

where ℓ is the simulation step counter, T_{sim} the simulation time step, $x_i(\ell)$ the longitudinal position of the rear 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 $a_{\text{dec,max}}$.

4.4.2 Longitudinal Models for Human Drivers

Now we describe the longitudinal behavior of the vehicles. First we consider models for human drivers, and in the next subsection we discuss models for the IVs and for the platoons. For human-driver models 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:

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

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 driver's desired or legal maximum speed. 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, $\sigma = \frac{T_{\text{react}}}{T_{\text{sim}}}$ is an integer.

- *Car-following model*: As described in (*15*) there exist various types of car-following models such as stimulus response models, collision avoidance models, psychophysical models, and cellular automata models.

  We will use a stimulus response model to describe the behavior of human drivers. 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 (*16*) 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 given by

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

  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 T_{delay}, which typically has a value of 1–1.2 s, is an integer multiple of T_{sim}. So, $d = \frac{T_{\text{delay}}}{T_{\text{sim}}}$ is an integer.

4.4.3 Longitudinal Models for Platoons

In our approach, the intelligent vehicles within the platoons 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:

- *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:

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

  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 ACC system to maintain short intraplatoon distances. The ACC algorithm consists of a combined speed and distance controller:

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

  where K_2 and K_3 are constants, and $h_{\text{ref},i}$ is the reference distance headway for vehicle i. Note that the speed controller is based on the same principle as the one used in the platoon leader model, but with the speed of the platoon leader as the reference speed. 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 headway 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.

4.4.4 Merging at On-Ramps and Lane Changing for Human Drivers

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 (see, e.g., (*17*) for more detailed models).

For individual human-driven vehicles (cf. the case study of Section 5 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. If both conditions are satisfied then the vehicle 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.

4.4.5 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 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).

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.

5 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 3 is applied. First, we will describe the set-up and the scenario used to evaluate the performance of the proposed approach, the prediction and simulation models used, as well as other implementation details. Next, we will discuss and analyze the results obtained from the simulations.

5.1 Set-Up

To illustrate the proposed MPC approach for the roadside controller we use a basic set-up consisting of a 6 km two-lane highway stretch with one mainstream origin, one on-ramp (located at position $x = 3.5$ km), and one destination (see Figure 3). The stretch consist of 6 sections with a length of 1 km each. We 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, on-ramp release times, and lane allocations for the platoons as control measures.

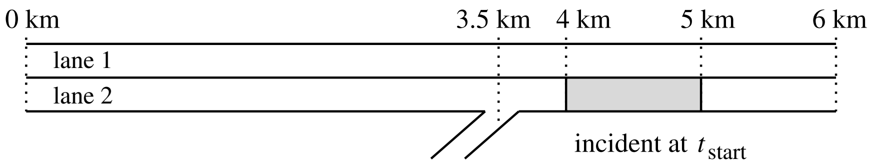


FIGURE 3 Set-up of the case study.

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.

5.2 Scenario

We simulate a period of 10 min starting at time $t_{\text{start}} = 7$ h 20 min and ending at time $t_{\text{end}} = 7$ h 30 min. The demand of vehicles is taken to be constant during the simulation period, and equals 1250 veh/h/lane for the mainstream origin and 350 veh/h for the on-ramp.

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 2, resulting in a blockage in lane 2 from position $x =$ 4 km up to position $x = 5$ km at time t_{start}. In the upstream sections 2 and 3 (i.e., from position $x = 2$ km up to $x = 4$ km) the initial density is 20 veh/km/lane, and in the other sections there are no vehicles. 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 region.

5.3 Models

As indicated above, we are interested in comparing the simulation results obtained for the given scenario using human driving (both without and with control) and using our platoon-based hierarchical approach. For this purpose, 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 4.4. In particular, we have used (2)–(3) with the reference accelerations given by respectively (4)–(5) (with $v_{\text{ref},i}(\ell)$ equal to the legal speed limit of 120 km/h) for uncontrolled human drivers, (4)–(5) (with $v_{\text{ref},i}(\ell)$ 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., then the various parameters in these models have the following values (these values inspired by the MITSIM model (*18*)): For the car-following model (5) 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 (7)–(8) we have $K_2 = 0.3$, $K_3 = 1$, $S_0 = 0.5$, and $T_{\text{head}} = 0.2$ for all vehicles. Moreover, $a_{\text{acc,max}} = 3$ and $a_{\text{dec,max}} = -5$ 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 (5) equal to $d = 4$ for the first vehicle that leaves the situation, and by reducing this reaction delay every sample 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.

5.4 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, lane allocations (for the platoons), and on-ramp metering as the control handles. The TTS for the entire simulation period can be expressed as

$$J_{\text{TTS,sim}} = \sum_{\ell=0}^{N_{\text{sim}}} \big(n_{\text{veh}}(\ell) + q_{\text{main}}(\ell) + q_{\text{on}}(\ell)\big) T_{\text{sim}} \quad , \tag{9}$$

where $N_{\text{sim}} = 600$ is the total number of simulation steps (of length $T_{\text{sim}} = 1$ s) within the entire simulation period of 10 min, $n_{\text{veh}}(\ell)$ is the number of vehicles that are present within the network at time $t = \ell T_{\text{sim}}$, $q_{\text{main}}(\ell)$ is the number of vehicles in the queue at the mainstream origin at time $t = \ell T_{\text{sim}}$, and $q_{\text{on}}(\ell)$ is the number of vehicles present in the on-ramp queue at time $t = \ell T_{\text{sim}}$.

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

$$J_{\text{perf}}(k) = \sum_{\ell=kM}^{(k+N_{\text{p}})M} \big(n_{\text{veh}}(\ell) + q_{\text{main}}(\ell) + q_{\text{on}}(\ell)\big) T_{\text{sim}} \quad ,$$

with $M = \dfrac{T_{\text{ctrl}}}{T_{\text{sim}}}$ (note that as we will select the control time step T_{ctrl} to be an integer multiple of the simulation time step T_{sim}, M will be an integer). In the total MPC objective function we also include a penalty term with $\alpha = 0.02$ (cf. (1)).

For the controlled human situation the applied control measures are (conventional) on-ramp metering and ISA (with one speed limit for each section of 1 km length between position $x = 0$ km and position $x = 4$ km). For the platoon-based approach 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 prediction period as well as the on-ramp release times for the platoons at the on-ramp during the prediction period. As in this case study we focus on dynamic speed limits and lane allocations for each platoon and on on-ramp metering, the platoon size is not yet considered to be a control variable, but it is kept fixed at 20 for all platoons.

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:

$$S_{0,\text{platoon}} + T_{\text{head,platoon}}\, v_{\text{platoon},p_1} \quad ,$$

where v_{platoon,p_1} is the speed of platoon p_1. For the case study we have selected $S_{0,\text{platoon}} = 20$ m and $T_{\text{head,platoon}} = 2$ s. Moreover, we consider a maximum speed of 120 km/h for both the human drivers and the platoon leaders.

TABLE 1 Results for the Three Approaches

Case	TTS (veh.h)	Relative improvement
uncontrolled case	71.18	0 %
controlled (human drivers)	63.38	10.96 %
controlled (platoons)	57.75	18.86 %

The control time step T_{ctrl} is set at 1 min. For the prediction horizon N_{p} we have taken a value that corresponds to 6 min, and for the control horizon N_{c} we have selected a value that corresponds to 3 min so as to limit the number of optimization variables.

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 `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 the `glcFast` command of the Matlab/Tomlab toolbox (*19*) for the mixed integer optimization problems (i.e., the determination of the speeds, on-ramp release times, and lane allocation for the platoon case).

5.5 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 1. In particular, we indicate the total time spent by all vehicles in the network during the entire simulation period of 10 min.

The results can be explained as follows. In the uncontrolled case with human drivers, when a driver is confronted with an incident on the same lane (lane 2), he starts to decelerate in order to avoid a collision. In case there is no space in lane 1 or in case the speed on lane 1 is almost the same as on lane 2, the driver waits and stays on lane 2 until the incident eventually gets cleared. However, once there is a possibility to perform a safe lane change maneuver, the driver moves to lane 1. 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 1 due to the effects of the incident in lane 2 causes congestion, which in its turn leads to a capacity drop for vehicles leaving the traffic jam. 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.

For the case with human drivers, ISA, and ramp metering, the MPC approach can predict the presence of the incident 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 incident. The main goals of speed limit control are to delay vehicles and to prevent them from entering the congestion (since the congestion will be dissolved or at least less severe by the time the vehicles then reach the congested area) and to provide entry space for the on-ramp vehicles. Ramp metering regulates the traffic flow entering via the on-ramp, so that it does not cause a further increase in congestion. This controlled approach with human drivers, ISA control, and ramp metering yields an improvement in TTS over the uncontrolled case of about 11 %.

For the platoon-based approach there are additional performance improvements caused by the optimal lane allocation and the full automation in addition to speed limits and ramp metering. The main idea behind speed limit control and on-ramp release time control is the same as for human controlled approach. However, the lane allocation control measure 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. Moreover, the full automation with IV technologies allows to maintain small intervehicle distances (so that more cars are allowed to traverse the network more quickly) even when in the case of congestion and it results in an almost 0 % capacity drop. The IV-based traffic with platoons results in the best performance with an improvement of about 19 % with respect to the uncontrolled case and of about 9 % with respect to the controlled human case.

6 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 Intelligent Vehicle Highway Systems (IVHS). The proposed approach has been illustrated using a case study based on simulations and 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 IVHS.

Future research topics include: additional and more extensive case studies, inclusion of additional control measures, development of efficient algorithms, assessment of the effects of model mismatches, explicit consideration of the other levels in the IVHS control hierarchy of (*7*), and extension to larger networks.

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