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Optimal Routing for Intelligent Vehicle Highway Systems Using a Macroscopic Traffic Flow Model

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

***Abstract*— We consider Intelligent Vehicle Highway Systems (IVHS) consisting of automated highway systems on which intelligent vehicles organized in platoons drive to their destination, controlled by a hierarchical control framework. In this framework there are roadside controllers that manage single stretches of highways. A collection of highways is then supervised by so-called area controllers. We focus on the optimal route choice control problem for the area controllers. In general, this problem is a nonlinear integer optimization problem with high computational requirements, which makes the problem intractable in practice. Therefore, we first propose a simplified but fast simulation model to describe the flows of platoons in the network. This model is a modified version of the macroscopic METANET traffic flow model, adapted to the case of platoons. Next, we use this model in a model-based predictive control approach in order to determine optimal splitting rates at the network nodes. These splitting rates can subsequently be communicated to the roadside controllers, which translate them into actual route instructions for the individual platoons.**

I. Introduction

Due to the ever-increasing demand for mobility and transportation, traffic congestion is a growing problem throughout the world. There are many possible approaches to reduce the frequency and impact of traffic jams (such as building new roads, introducing road pricing policies, stimulating modal shift, promoting public transportation, etc.). On the longer term one of the most promising approaches is the integrated use of traffic management and control systems, called Intelligent Vehicle Highway Systems (IVHS), that incorporate intelligence in both the roadside infrastructure and in the vehicles.

In IVHS all vehicles are assumed to be fully automated with throttle, braking, and steering commands being determined by automated on-board controllers. This complete automation of the driving tasks allows to organize the traffic in platoons, i.e., a closely spaced group of vehicles traveling together with short intervehicle distances [1]. Platoons can travel at high speeds and to avoid collisions between platoons at these high speeds, a safe interplatoon distance of about 20–60 m should be maintained. Moreover, the vehicles in each platoon travel with small intraplatoon distances of about 2–5 m, which are maintained by the automated on-board speed and distance controllers using Adaptive Cruise Control (ACC). By traveling at high speeds while maintaining short intraplatoon distances, the platoon approach allows more vehicles to travel on the network, which improves the traffic throughput [2], [3].

In [4] we have proposed a hierarchical traffic management and control framework for IVHS that builds upon earlier research in this field such as the PATH framework [1]. The control architecture of [4] consists of a multi-level control structure with local controllers at the lowest level and one or more higher supervisory control levels (see also Figure 1). In this paper, we will in particular concentrate on how the area controllers can determine optimal routes for the platoons using optimal control. In general this leads to a nonlinear mixed-integer optimization problem. However, by considering a simplified model to describe the behavior of the platoons in the network, the problem can be recast into an optimization problem that only involves real-valued variables, which leads to a significant improvement in computational efficiency. More specifically, the model we propose is a modified version of the macroscopic traffic flow model METANET [5], [6], which is adopted to fit the IVHS and platoon framework.

This paper is organized as follows. In Section II we briefly revisit the hierarchical traffic management and control framework of [4]. Next, we focus on the route guidance tasks of the area controllers. In Section III we introduce the new macroscopic traffic flow model for platoons based on the METANET model. This model is then embedded in a model-based predictive control approach for optimal route guidance by the area controllers in Section IV. Section IV-A presents a simple example that illustrates the proposed approach, and Section V concludes the paper.

II. Intelligent vehicle highway systems (IVHS)

We now briefly present the hierarchical control framework for IVHS we have proposed in [4]. This framework is based on the platoon concept and it distributes the intelligence between roadside infrastructure and vehicles using control measures such as intelligent speed adaption, adaptive cruise control, lane allocation, on-ramp access control, route guidance, etc. The control architecture of [4] consists of a multi-level 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 hierarchical control framework can be characterized as follows:

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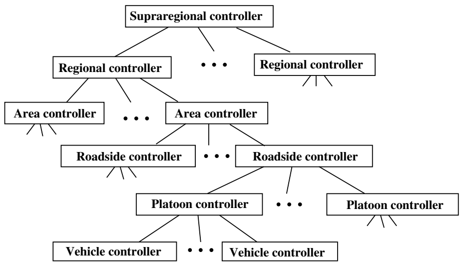


Fig. 1. The hierarchical control framework of [4] for IVHS

- The *higher-level controllers* (such as area, regional, and supraregional controllers) provide network-wide coordination of the lower-level and middle-level controllers. In particular, the area controllers provide area-wide dynamic route guidance for the platoons, and they supervise and coordinate the activities of the roadside controllers in their area by providing set-points and control targets. In turn, a group of area controllers could be supervised by regional controllers, and so on.
- The *roadside controllers* may control a part of a highway or an entire highway. The main tasks of the roadside controllers are to assign speeds for each platoon, safe distances to avoid collisions between platoons, and ramp metering values at the on-ramps. The roadside controllers also give instructions for merging, splitting, and lane changes to the platoons.
- The *platoon controllers* receive commands from the roadside controllers and are responsible for control and coordination of each vehicle inside the platoon. These 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 (for intelligent speed adaption), headways (for adaptive cruise control), and paths) and they translate these commands into control signals for the vehicle actuators such as throttle, braking, and steering actions.

In [7], [8] we have proposed model predictive control methods for the roadside controllers to determine optimal speeds, lane allocations, and on-ramp release times for the platoons. In the remainder of the paper we will focus on the area controllers and in particular on how optimal routes can be determined for the platoons.

In principle, the optimal route choice control problem in IVHS consists in assigning an optimal route to each individual platoon in the network. However, this results in a huge nonlinear integer optimization problem with high computational complexity and requirements, making the problem in fact intractable in practice. Since considering each individual platoon is too computationally intensive for on-line real-time control, we will consider a more aggregate model based on the METANET model.

III. A MACROSCOPIC METANET-BASED MODEL FOR IVHS

In general, macroscopic traffic flow models consider the traffic flow as a continuum, i.e., a fluid or gas with specific characteristics [9], [10] using aggregated variables like mean speed, flow, density, etc. to describe the dynamics of traffic flow. There exists a wide variety of macroscopic traffic flow models [10], [11]. Since the METANET model has been used extensively for model-based control (see, e.g., [5], [12]–[14]) and since it can quite easily be extended to fit the IVHS/platoon framework, we propose a platoon-based version of the METANET model in this section. First, we discuss the effect of using platoons on the macroscopic traffic flow characteristic, in particular, on the fundamental diagram.

A. Macroscopic traffic flow characteristics and intelligent vehicles

In macroscopic models the flows in a traffic network are characterized by aggregated variables such as the mean speed v, the mean traffic density ρ, and the mean traffic flow q for a given segment and a given time span. In general, these three quantities are related by the fundamental relation

$$q = \rho v \quad . \tag{1}$$

For human drivers the (equilibrium) relation between the speed v and the density ρ can be modeled as [15]:

$$V(\rho) = v_{\text{free}} \exp\left[-\frac{1}{a}\left(\frac{\rho}{\rho_{\text{crit}}}\right)^{a}\right] \quad . \tag{2}$$

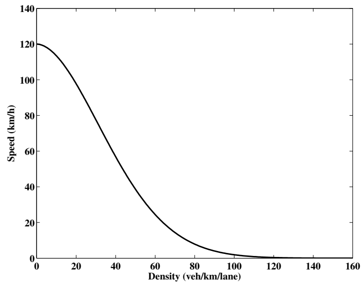
where ρ_{crit} is the critical density (i.e., the density at which the flow is maximal), v_{free} is the free-flow speed, and a is a model parameter. Typical values for these parameters are v_{free}=120 km/h, ρ_{crit}=33.5 veh/km/lane, and $a = 1.867$ [12]. The fundamental relation given in (2) can be depicted using the so-called fundamental diagram shown in Figure 2 for a single lane. This figure shows the maximum flow $q_{\max}$, and the critical density ρ_{crit}.

When semi-automatic or intelligent vehicles are used on the road, the macroscopic traffic flow will change. An example of such a change is given by Bose et al. [16], where Adaptive Cruise Control (ACC) is considered with a constant time headway policy. The constant time headway policy is the control form most often used for ACC [16]–[18]. The spacing is given in [18] as

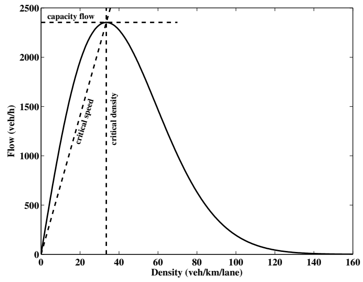
$$s_i = h_{\text{des}} v_i + L_i \quad ,$$

where s_i is the space headway for vehicle i (i.e., the distance difference in position between the rear of vehicle i and the rear of its predecessor), h_{des} is the desired time headway, v_i is the velocity of vehicle i, and L_i is the length of the vehicle.

If s is the average space headway in a given segment or link, then the corresponding density ρ is given by $\rho = \dfrac{1}{s}$. This implies that for a given speed v, a given average space headway s, and a given average vehicle length L, the maximal



(a) Speed-density plot



(b) Flow-density plot

Fig. 2. Fundamental diagram for human drivers

density $\rho_{\rm ACC}$ with ACC-controlled intelligent vehicles can be expressed as:

$$\rho_{\rm ACC} = \frac{1}{s} = \frac{1}{h_{\rm des} v + L} \quad . \tag{3}$$

Rewriting (3) gives an expression for the (maximally possible) speed as

$$v = \frac{1}{h_{\rm des}} \left(\frac{1}{\rho_{\rm ACC}} - L \right) \quad .$$

Now taking into account that the speed cannot exceed the free-flow speed $v_{\rm free}$, the expression for the desired speed using ACC-equipped vehicles only becomes

$$v_{\rm ACC} = \begin{cases} v_{\rm free} & \text{if } \rho \leq \rho_{\rm ACC,crit}\,, \\ \frac{1}{h_{\rm des}} \left(\frac{1}{\rho} - L \right) & \text{if } \rho > \rho_{\rm ACC,crit}\,. \end{cases} \tag{4}$$

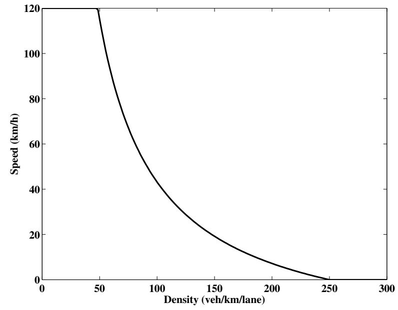
For a situation with ACC-equipped intelligent vehicles only the critical density $\rho_{\rm ACC,crit}$ at which the maximal flow is obtained, is thus given by:

$$\rho_{\rm ACC,crit} = \frac{1}{h_{\rm des} v_{\rm free} + L} \quad .$$

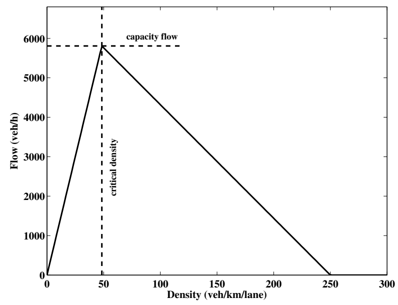
Using (4) and (1) the relation between the flow and density becomes

$$q_{\rm ACC} = \begin{cases} \rho v_{\rm free} & \text{if } \rho \leq \rho_{\rm ACC,crit}\,, \\ \frac{1}{h_{\rm des}} (1 - \rho L) & \text{if } \rho > \rho_{\rm ACC,crit}\,. \end{cases}$$

For typical values of $h_{\rm des}$=0.5 s, L=4 m, and $v_{\rm free}$=120 km/h, we obtain $\rho_{\rm ACC,crit}$=48.39 veh/km and the speed-density and flow-density curves shown in Figure 3. The flow-density curve illustrates that platoons of ACC-equipped intelligent vehicles will yield a better performance than human drivers, and it also shows that the maximum flow is more than doubled.



(a) Speed-density plot



(b) Flow-density plot

Fig. 3. Fundamental diagram for ACC-equipped intelligent vehicles

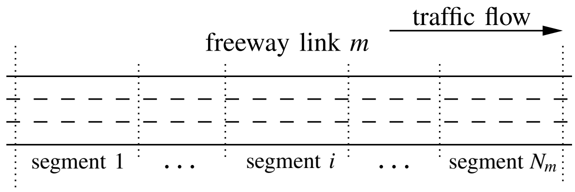


Fig. 4. In the METANET model a freeway link is divided into segments

B. *A METANET-like model for platoons in IVHS*

The METANET model is a second-order macroscopic traffic flow model that has been proposed by Papageorgiou and his co-workers [6]. Since we will use the METANET model for solving routing problems, we will use the destination-oriented version of the METANET, which explicitly models the traffic flow with routing choices for multiple origin and destinations and associates splitting rates for each reachable destination from a node. In the case of human drivers the splitting rates are determined by an autonomous process called traffic assignment. However, in the case of IVHS the splitting rates can considered as a controllable input.

The METANET model represents a network as a directed graph with the links corresponding to freeway stretches as shown in Figure 4. Where major changes occur in the characteristics of the link or in the road geometry (e.g., on-ramp or an off-ramp), a node is placed.

1) Link model: In the METANET each link m is divided into N_m segments with length L_m. The number of lanes on link m is denoted by λ_m. The traffic flow in segment i of link m destined to a destination j is characterized by three macroscopic variables:

- mean speed $v_{m,i}(k)$ [km/h]

- partial density $\rho_{m,i,j}(k)$ [veh/km/lane]
- traffic flow $q_{m,i}(k)$ [veh/h]

where k is the discrete time instant $t = kT$ where T is the simulation time step (typically around 10 seconds). At time step k, the partial density $\rho_{m,i,j}(k)$ describes the density in the segment i of link m that is traveling to destination j.

For each segment in a link, for all possible destinations reachable via the link, the conservation of vehicles in a segment can be expressed as

$$\rho_{m,i,j}(k+1) = \rho_{m,i,j}(k) + \frac{T}{L_m\lambda_m}\left(\gamma_{m,i-1,j}(k)q_{m,i-1}(k) - \gamma_{m,i,j}(k)q_{m,i}(k)\right) \quad ,$$

where $q_{m,i-1}(k)$ is the traffic flow that flows out of segment $i-1$ of link m into segment i for simulation time step k, $q_{m,i}(k)$ is the flow out of segment i of link m, and $\gamma_{m,i,j}(k)$ is the composition rate for the traffic flow in segment i of link m with destination as j at simulation time step k,

The mean speed in segment i of link m at the next discrete time step $k+1$ is given by

$$\begin{aligned} v_{m,i}(k+1) = v_{m,i}(k) &+ \frac{T}{\tau}\Big(V\big(\rho_{m,i}(k)\big) - v_{m,i}(k)\Big) \\ &+ \frac{T}{L_m} v_{m,i}(k)\big(v_{m,i-1}(k) - v_{m,i}(k)\big) \\ &- \frac{\eta T}{\tau L_m}\frac{\rho_{m,i+1}(k) - \rho_{m,i}(k)}{\rho_{m,i}(k) + \kappa} \quad , \end{aligned} \tag{5}$$

where τ corresponds to the driver's response time and where η and κ are model parameters. For human drivers a typical value for τ is 18 s. For IVHS this value will be much lower, e.g., 8 s. Typical values for η and κ are[1] η=60 km^2/h and κ=40 veh/km/lane.
For human drivers, $V(\rho_{m,i}(k)$ is given by (cf. 2)

$$V(\rho_{m,i}(k)) = v_{\text{free},m} \exp\left[-\frac{1}{a_m}\left(\frac{\rho_{m,i}(k)}{\rho_{\text{crit},m}}\right)^{a_m}\right] \quad , \tag{6}$$

where a_m is a model parameter for the specific link m, $v_{\text{free},m}$ is the free-flow speed, and $\rho_{\text{crit},m}$ is the critical density.
The expression of $V(\rho_{m,i}(k)$ for platoons in an IVHS is given by (cf. (4)):

$$V(\rho_{m,i}(k)) = \begin{cases} v_{\text{free}} & \text{if } \rho_{m,i}(k) \leq \rho_{\text{ACC,crit},m}\,, \\ \frac{1}{h_{\text{des}}}\left(\frac{1}{\rho_{m,i}(k)} - L\right) & \text{if } \rho_{m,i}(k) > \rho_{\text{ACC,crit},m}\,. \end{cases} \tag{7}$$

2) Origin model: Origins are modeled using a simple queue model. A queue is formed at origin o when the traffic demand $d_o(k)$ exceeds the service rate $q_o(k)$ of the origin. The queue length $w_{o,j}(k+1)$ destined to destination j at origin o can be determined from the previous queue length and the total demand $d_o(k)$ at time step k as follows:

$$w_{o,j}(k+1) = w_{o,j}(k) + T\gamma_{o,j}(k)\left(d_o(k) - q_o(k)\right) \quad ,$$

[1]These are values for human drivers, for IVHS these values might be somewhat higher.

with $\gamma_{o,j}(k)$ is the fraction of the demand traveling to destination j from origin o. The outflow at origin $q_o(k)$ can be expressed as:

$$q_o(k) = \min\left[d_o(k) + \frac{w_o(k)}{T}, Q_{\text{cap},o}\min\left(1, \frac{\rho_{\max} - \rho_{\mu,1}(k)}{\rho_{\max} - \rho_{\text{crit},\mu}}\right)\right]$$

where $Q_{\text{cap},o}$ is the capacity (veh/h) of the origin o under free-flow conditions, $\rho_{\max}$ is the maximum density of a segment, and μ is the index of the link to which the origin is connected.

3) Node model: The node model describes how the traffic should be routed among the set of entering and leaving links of a node. For a given node n, let I_n denote the set of input links, and let O_n denote the set of output links. The traffic flow $Q_{n,j}(k)$ with destination j that enters the node n at simulation step k is distributed to the output links according to

$$Q_{n,j}(k) = \sum_{\mu \in I_n} q_{\mu,N_\mu}(k)\gamma_{\mu,N_\mu,j}(k) \tag{8}$$

$$q_{n,m,\text{out}}(k) = \sum_{j \in J_m} \beta_{n,m,j}(k)Q_{n,j}(k) \quad , \tag{9}$$

where $q_{\mu,N_\mu}(k)$ is the flow leaving the last segment of link μ, $\beta_{n,m,j}(k)$ is the splitting rate in node n that is defined as the fraction of the traffic flow heading towards destination j that leaves node n via output link m, J_m is the set of destinations that are reachable through link m, and $q_{n,m,\text{out}}(k)$ is the total traffic flow that leaves node n via output link m at step k.

The composition rate $\gamma_{n,m,\text{out},j}(k)$ of the traffic flow out of node n into link m is given by:

$$\gamma_{n,m,\text{out},j}(k) = \frac{\beta_{n,m,j}(k)Q_{n,j}(k)}{q_{m,\text{out}}(k)} \quad .$$

We capture the effect of the downstream density of the output links leaving node n by the following expression:

$$\rho_{m,N_{m+1}}(k) = \frac{\sum_{\mu \in O_n}\rho^2_{\mu,1}(k)}{\sum_{\mu \in O_n}\rho_{\mu,1}(k)} \quad ,$$

where $\rho_{\mu,1}(k)$ is the density of the first segment of output link μ. Similarly when a node n has many input links, then the upstream speed is captured by adding a virtual segment at the beginning of the link and by setting

$$v_{m,0}(k) = \frac{\sum_{\mu \in I_n} v_{\mu,N_\mu}(k)q_{\mu,N_\mu}(k)}{\sum_{\mu \in I_n} q_{\mu,N_\mu}(k)} \quad ,$$

where N_μ is the index of the last of last segment of link μ.

IV. Model predictive route choice control

We can use the model of the previous subsection to derive a model-based predictive approach that can be used by the area controllers to determine the optimal splitting rates.

More specifically, we adopt the model predictive control (MPC) scheme [19] (see Figure 5). At each control step k the state of the traffic system is measured or estimated, and an optimization is performed over the prediction horizon $[kT, (k+N_\text{p})T]$ to determine the optimal control inputs,

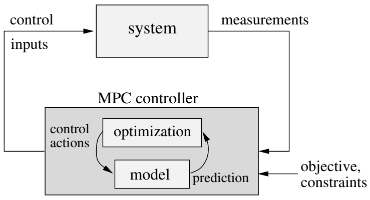


Fig. 5. Schematic view of the MPC approach

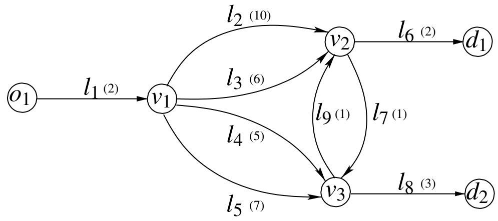


Fig. 6. Set-up of case study network

Period (min)	0–10	10–30	30–40	40–60
D_{o_1,d_1} (veh/h)	5000	8000	2500	0
D_{o_1,d_2} (veh/h)	1000	2000	1000	0

TABLE I
DEMAND PROFILES USED IN THE CASE STUDY

where N_p is the prediction horizon. Only the first value of the resulting control signal (the control signal for time step k) is then applied to the process. At the next control step $k+1$ this procedure is repeated.

To reduce complexity and improve stability often a control horizon N_c ($\leq N_\mathrm{p}$) is introduced in MPC, and after the control horizon has been passed the control signal is taken to be constant. So there are two loops: the rolling horizon loop and the optimization loop inside the controller. The loop inside the controller of Figure 5 is executed as many times as needed to find the optimal control signals at control step k, for the given N_p, N_c, traffic state, and expected demands. The loop connecting the controller and the traffic system is performed once for each control step k and provides the state feedback to the controller. This feedback is necessary to correct for (the ever present) prediction errors, and to provide disturbance rejection (compensation for unexpected traffic demand variations). The advantage of this rolling horizon approach is that it results in an on-line adaptive control scheme that allows us to take changes in the system or in the system parameters into account by regularly updating the model of the system.

For our case the control variables in this set-up are the splitting rates at the nodes with more than one outgoing link (and if speed limits are included, also these speed limits). The optimization variables include the control variables as well as the state variables of the macroscopic METANET-like traffic flow model for IVHS derived above.

A typical objective function to be used is the total time spent (TTS) by all the vehicles in the network. This includes both the time spent traveling through the network and the time spent waiting in the queues, if any. Minimizing TTS then results in a nonlinear nonconvex optimization problem with real-valued variables. To solve the nonlinear optimization problem we can use a global or a multi-start local optimization method such as multi-start sequential quadratic programming, pattern search, genetic algorithms, or simulated annealing.

A. Case study

In this subsection we present a simple case study involving a basic set-up to illustrate the area-level control approach for IVHS proposed in this section. First, we will describe the set-up and the details of the scenario used for our simulations. Next, we will discuss and analyze the obtained results.

1) Scenario: We consider a simple network of highways with one origin o_1 and two destinations d_1, d_2, and three internal nodes v_1, v_2, and v_3 (see Figure 6). The network of Figure 6 consists of three links connecting o_1 to v_1, v_2 to d_1, and v_3 to d_2, as well as six links connecting the internal nodes allowing four possible routes to each destination (e.g., d_1 can be reached via l_2, l_3, l_4+l_9, and l_5+l_9). In Figure 6, the values within brackets indicates the number of segments (N_m) in the particular link. The length of a segment (L_m) in any link is taken to be 1 km.

We consider four different cases (due to the use of two fundamental diagrams):

- Case A: no control case with human drivers,
- Case B: controlled case with humans drivers,
- Case C: controlled case with platoons.

For all the links we use the following values for the parameters of the METANET(-like) model: v_free=120 km/h, $a = 1.867$, κ=40 veh/km/lane and η=60 km^2/h. For the human drivers case we use ρ_crit=33.5 veh/km/lane, τ=18 s, and the fundamental V–ρ relation (6), while for the IV case we use ρ_crit =48.39 veh/km/lane, τ=8 s, and the fundamental V–ρ relation (7).

We simulate a period of 60 min. The simulation time step T is set to 20 s. The demand pattern is piecewise constant during the simulation period and is given in Table I. The demand to be processed in the period [10,30] higher than the capacity of the network, giving rise to an origin queue for each destination. For the proposed scenario the initial state of the network is taken to be empty. We choose $N_\mathrm{p} = 20$ and $N_\mathrm{c} = 6$. For the sake of simplicity we take the simulation model to be equal to the prediction model.

2) Control problem: The control variables considered for this case study are the splitting rates $\beta_{n,m,j}(k)$ associated with all reachable destinations via outgoing links for each internal node for $k = 0,1,\ldots,N_\mathrm{sim}-1$ where N_sim = 180 is the total number of simulation steps (of length T = 20 s) within the entire simulation period of 60 min.

Since it makes no sense to send vehicles reaching node v_2 that are going to destination 1, towards link l_7 we set $\beta_{v_2,l_6,1}(k) = 1$ and $\beta_{v_2,l_7,1}(k) = 0$ for all k. Likewise, we set $\beta_{v_2,l_6,2}(k) = 0$ and $\beta_{v_2,l_7,2}(k) = 1$ for all k. For node v_3 we have: $\beta_{v_3,l_8,1}(k) = 0$ and $\beta_{v_3,l_9,1}(k) = 1$, $\beta_{v_3,l_8,2}(k) = 1$, $\beta_{v_3,l_9,2}(k) = 0$ for all k. So in fact the optimization variables are $\beta_{v_1,m,j}(k)$ for $m = l_2, l_3, l_4, l_5$ and $j = 1,2$.

We have the following constraints:

$$\beta_{v_1,l_2,j}(k) + \beta_{v_1,l_3,j}(k) + \beta_{v_1,l_4,j}(k) + \beta_{v_1,l_5,j}(k) = 1$$

for $j = 1,2$ and for all k.

The goal of our area controller is to improve the traffic performance. The objective that we consider for our case study is minimization of the total time spent (TTS) by all the vehicles in the network using routing as the control measure. The TTS for the entire simulation period can be expressed as:

$$J_{\mathrm{TTS,sim}} = \sum_{k=0}^{N_{\mathrm{sim}}-1} \left(\sum_{(m,i)\in\mathscr{L}_{\mathrm{ls}}} \rho_{m,i}(k) L_m \lambda_m + \sum_{(o,j)\in\mathscr{O}_{\mathrm{od}}} w_{o,j}(k) \right) T \, ,$$

where $\mathscr{L}_{\mathrm{ls}}$ is the set of all link-segment index pairs (m,i), and $\mathscr{O}_{\mathrm{od}}$ the set of all origin-destination pairs (o,j).

3) Results and analysis: In case of no control (Cases A and B), the capacities of the direct links l_1, l_2, l_3, and l_4 are consumed up to their maximum while the links l_7 and l_9 are not used due to the fact that all vehicles and platoons want to take the shortest routes. At the point when the demand exceeds the maximum capacity of the links, origin queues are formed. As the simulation advances, the queue length increases with time, thus leading to a huge total time spent.

For the controlled cases (Cases B and C) the area controller assigns the splitting rates at the internal node v_1 and routes the traffic flow (human drivers or platoons) in a system-optimum manner such that the traffic performance is improved. When platoons of ACC-equipped vehicles are deployed in the traffic system, the traffic performance is improved more than the human drivers case. For these cases we have used the SQP function SNOPT, implemented via the function `snopt` of the Matlab Tomlab toolbox, to compute the optimal splitting rates. Compared to Case A this results in a performance improvement of about 3 % for Case B and of about 46 % for Case C.

V. Conclusions

We have considered the optimal route guidance problem for IVHS using a hierarchical setting in which area controllers coordinate the routes of the platoons in the network. Since in general this results in a nonlinear mixed-integer optimization problem, we have proposed a simplified model to describe the flow of platoons in IVHS based on the macroscopic METANET traffic flow model, which has been adapted to fit the case of platoons of intelligent vehicles equipped with Adaptive Cruise Control (ACC). The resulting model has subsequently been used in a model-based predictive control approach for determining optimal splitting rates of the platoon flows at the nodes in the network. This leads to a nonlinear optimization problem with real-valued variables, for which efficient solvers exist. Once the optimal splitting rates have been determined by the area controller, they are sent to the lower-level roadside controllers, which can then translate them into actual route instructions for the platoons. The proposed approach has been illustrated via a simple case study.

In our future research, we will also consider additional case studies and assess the performance improvement of the proposed approach with respect to an approach based on mixed-integer optimization. We will also investigate the coordination and mutual interaction between various area controllers and between the area and the roadside controllers.

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