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Integration of Dynamic Route Guidance and Freeway Ramp Metering Using Model Predictive Control

Abdes Karimi, Andreas Hegyi, Bart De Schutter, Hans Hellendoorn, and Frans Middelham

Abstract— **We propose a traffic control approach that integrates ramp metering and of dynamic route guidance using a model predictive control framework. The main objective of the control is to minimize the Total Time Spent (TTS) in the network by providing accurate travel times shown the Dynamic Route Guidance Panels (DRIPs) as controller input to the traffic network while taking into account the effect of other traffic control measures, such as ramp metering. By aiming at minimizing the TTS as well as the difference between travel times shown on the DRIPs and the travel times actually realized by the drivers, the interests of both the individual drivers as well as the road administration are pursued. Simulation results for a case study show that the proposed integrated MPC traffic control results in a lower TTS while the drivers get accurate travel time information.**

I. Introduction

One solution to the ever growing traffic congestion problem is to extend the road network. Adding lanes and creating alternative new freeway connections is possible but rather expensive. Dynamic traffic management is an alternative that aims to increase the safety and efficiency of the existing traffic networks. Several dynamic traffic management measures have been developed and implemented, such as ramp metering systems, Dynamic Route Guidance Information Systems (DRGIS), variable speed limits, etc. In this paper we focus on ramp metering and DRGIS.

Ramp metering systems consist of traffic signals that are positioned at on-ramps of freeways and that can be used to regulate the flow of traffic entering the freeway from the on-ramp. DRGIS are used to inform drivers about current or expected travel times and queue lengths so that they may reconsider their choice for a certain route.

In the field of traffic control one usually considers predicted or instantaneous travel times as the system input, but this paper considers optimized travel times as the system input (control signal). Instantaneous travel times are travel times based on the current traffic state. In case there are no major changes in the traffic state during the trip from the DRGIS to the destination, these travel times are a good approximation of the travel times actually realized by drivers from the DRGIS to the destination. However, in case the traffic state changes due to the traffic dynamics, the instantaneous travel times are not reliable anymore. By using predicted travel times the future state of the traffic network is also taken into account. However, showing predicted travel times on DRGIS panels and the resulting rerouting by the drivers may result in a traffic distribution that is not always optimal with respect to the total network performance. Another drawback is that other traffic control measures on the traffic network are not taken into account. Therefore, in this paper *optimized* travel times are introduced, which are optimized in combination with and at the same time as the other control signals.

Combination of on-ramp metering and dynamic route guidance with the use of an optimal control strategy has been studied in [1], [2]. There, optimal split rates at points where drivers can choose between alternatives are calculated using METANET-DTA, and the ramp metering rates are calculated with the ALINEA feedback algorithm or also taken into account within the optimization routine. However, after calculating optimal split rates as done in [1], [2], it is rather hard to find those control measures that realize the optimal splitting rates.

We propose a network-wide control strategy based on the integration of DRGIS and ramp metering using Model Predictive Control (MPC) [3]. We will consider networks consisting of both freeways and secondary roads, and the control will also take the effects of ramp metering and DRGIS on the traffic situation on the secondary roads into account. The control signals we consider are ramp metering rates and travel times shown on the DRGIS. Usually these signals are determined separately using different objective functions, decomposition, or hierarchical optimization. However, we will optimize both types of signals at the same time using one objective function, which will result in a better overall performance. The travel times shown on the DRGIS and the ramp metering rates are optimized to minimize the objective function, which consists in minimizing the Total Time Spent (TTS) on the one hand, and in reducing the difference between the travel times shown on the DRGIS and the actually realized travel times. As a consequence, the drivers will be guaranteed a minimal but accurate travel time.

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II. TRAFFIC PREDICTION MODELS

The MPC approach we propose requires a model of the system in order to be able to predict how the traffic will evolve for given demands and control signals. The prediction model consists of three parts, describing respectively the evolution of the traffic flows (for which we use the METANET model), the reaction of the drivers to the route guidance, and the calculation of the travel times.

A. METANET model

METANET [4], [5] is a macroscopic traffic modeling and simulation tool. There are two possible ways to use METANET: in destination-oriented mode, and in non-destination-oriented mode. As we consider (re)routing of traffic, we will use the destination-oriented mode. For the sake of completeness, we will briefly present the destination-oriented METANET model below, with a focus on the parts of the model that are required for the case study of Section IV. For a more detailed explanation we refer to [4], [5], and to [6], [7], where some modifications to the METANET model are proposed.

In METANET the traffic network is defined as a directed graph with links and nodes, whereby the links represent the freeway segments. Each freeway segment has uniform characteristics. Nodes in the graph are placed at each location where changes take place. A freeway link m consists of N_m segments of equal length L_m (typically 300–1000 m). The number of lanes of link m is denoted by λ_m. Let T be the simulation time step, which must be chosen such that a vehicle cannot pass a link within one time step (so it typically has a value of about 10 s). For each segment i of each link m we define the following macroscopic variables for simulation step k, which are used to describe the state of the traffic network:

- the traffic density $\rho_{m,i}(k)$ (veh/km/lane) in segment i of link m at time $t = kT$,
- the mean speed $v_{m,i}(k)$ (km/h) of the vehicles in segment i of link m at time $t = kT$,
- the traffic flow $q_{m,i}(k)$ (veh/h) leaving segment i of link m in the time interval $[kT, (k+1)T]$.

In METANET the partial density $\rho_{m,i,j}(k)$ of vehicles in segment i of link m destined to j is updated as follows:

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

where $\gamma_{m,i,j}(k) = \frac{\rho_{m,i,j}(k)}{\rho_{m,i}(k)}$ is the fraction of the traffic in segment i of link m going to destination j and $\rho_{m,i}(k)$ the total traffic density in segment i of link m. Moreover,

$$q_{m,i}(k) = \rho_{m,i}(k)v_{m,i}(k)\lambda_m \tag{2}$$

$$v_{m,i}(k+1) = v_{m,i}(k) + \frac{T}{\tau}[V(\rho_{m,i}(k) - v_{m,i}(k)] + \frac{T}{L_m}v_{m,i}(k)[v_{m,i-1}(k) - v_{m,i}(k)] - \frac{\upsilon T}{\tau L_m}\frac{\rho_{m,i+1}(k) - \rho_{m,i}(k)}{\rho_{m,i}(k) + \kappa} \ , \tag{3}$$

where κ, υ and τ are freeway parameters and $V(\rho_{m,i}(k))$ is the desired speed:

$$V[\rho_{m,i}(k)] = v_{\mathrm{f},m}\exp\left[-\frac{1}{a_m}\left(\frac{\rho_{m,i}(k)}{\rho_{\mathrm{cr},m}}\right)^{a_m}\right] \ ,$$

where a_m is a model parameter, $v_{\mathrm{f},m}$ is the free flow speed for link m, and $\rho_{\mathrm{cr},m}$ is the critical density for link m.

In case a link is an on-ramp the modeling is done differently to allow the modeling of the queue. Let the portion $d_{o,j}(k)$ of the traffic demand $d_o(k)$ at on-ramp o that is destined to destination j be defined by $\theta_{o,j}(k)$:

$$d_{o,j}(k) = \theta_{o,j}(k)d_o(k) \ .$$

The allowed flow $\hat{q}_o(k)$ is calculated as

$$\hat{q}_o(k) = \min\left[\sum_{j\in J_o}\left(d_{o,j}(k) + \frac{w_{o,j}(k)}{T}\right), Q_o\min\left(1, \frac{\rho_{\max} - \rho_{\mu,1}(k)}{\rho_{\max} - \rho_{\mu,\mathrm{cr}}}\right)\right] \ ,$$

where J_o is the set of destinations reachable from on-ramp o, $w_{o,j}(k)$ is the length of the (sub)queue at on-ramp o of vehicles going to destination j, Q_o stands for the on-ramp's capacity under the condition that the freeway is free flow, and $\rho_{\max}$ is the maximum density. If there is no ramp metering at origin o, then the actual flow $q_o(k)$ leaving the on-ramp equals the allowed flow $\hat{q}_o(k)$. When ramp metering is present, the metering rate $r_o(k)$ defines which fraction of the allowed flow is actually admitted to the freeway: $q_o(k) = r_o(k)\hat{q}_o(k)$. Note that no metering corresponds to $r_o(k) = 1$ for all k. The subqueue length $w_{o,j}(k)$ is updated as follows:

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

The total traffic flow entering a given node n and destined to destination $j \in J_n$, where J_n is the set of destinations reachable from node n, is calculated as

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

where I_n is the set of incoming links for node n, and where N_μ refers to the last segment of incoming link μ. For the outgoing traffic, the part of the flow choosing link m to get to its destination j is calculated as the flow leaving the (virtual) 0th segment:

$$q_{m,0}(k) = \sum_{j\in J_m}\beta^m_{n,j}(k)Q_{n,j}(k) \ ,$$

where O_n is the set of outgoing links for node n, and $\beta^m_{n,j}(k)$ is the portion of the traffic flow from node n to destination j traveling via link m. Furthermore, we set

$$\gamma_{m,0,j}(k) = \frac{\beta^m_{n,j}(k)Q_{n,j}(k)}{q_{m,0}(k)} \ .$$

In case a node n connected to a link m has two or more leaving links, the upstream influence of the density is taken into account by setting

$$\rho_{m,N_{m+1}}(k) = \frac{\sum_{\mu \in O_n} \rho_{\mu,1}^2(k)}{\sum_{\mu \in O_n} \rho_{\mu,1}(k)} \quad , \tag{4}$$

where $\rho_{m,N_{m+1}}$ is the (virtual) density used in (3) for the last segment of link m. Expression (4) accounts for the effect of queue spill-back from a congested link into the entering link even if the other links are in free-flow state. In case of more than one incoming link to a node n, the downstream influence of the speed should be taken into account as:

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

where the virtual speed $v_{m,0}$ is required in (3) for the first segment of link m.

B. Driver route choice modeling

The METANET model presented in Section II-A above describes the evolution of the traffic flows in a traffic network. One of the variables in this model is the routing choice parameter β, which is the result of the drivers' behavior, and which in our case will be influenced by the travel times shown on the DRGIS panels. Hence, we also require a model that describes how drivers react to travel time information and how they adapt their route choice.

A well-known behavior model is the logit model [8]–[10], which is used to model all kinds of consumer behavior based on the cost of several alternatives. The lower the cost of an alternative, the more consumers will choose that alternative. In the traffic context, the consumers are the drivers, and the cost is the comfort, safety, or travel time of the possible alternative routes to the desired destination. The logit model calculates the probability that a driver chooses one of more alternatives based on the difference in travel time between the alternatives.

Assume that we have two possible choices m_1 and m_2 at node n to get to destination j (the extension to three or more alternative choices is possible, but not necessary for the case study of Section IV). For the calculation of the split rates out of the travel time difference between two alternatives the logit model results in

$$\beta_{n,j}^m(k) = \frac{\exp(\sigma(\vartheta_{n,j}^m(k)))}{\exp(\sigma(\vartheta_{n,j}^{m_1}(k))) + \exp(\sigma(\vartheta_{n,j}^{m_2}(k)))}$$

for $m = m_1$ or $m = m_2$, where $\vartheta_{n,j}^m(k)$ is the travel time shown on the DRGIS at node n to travel to destination j via link m. The parameter σ describes how drivers react on a travel time difference between two alternatives. The higher σ, the less travel time difference is needed to convince drivers to choose the fastest alternative route.

C. Calculation of individual travel times

The calculation of the individual travel times is necessary to determine the difference between the realized travel times and the travel times shown on the DRGIS. This calculation is inspired by [11], and is done by tracking vehicles at every simulation step. When a vehicle passes a bifurcation node with a DRGIS panel, that information is stored such that when the vehicle leaves the network its realized travel time can be computed, and the difference between the realized travel time and the travel time shown on the DRGIS can be included in the prediction error term of the performance function (see (5)).

Let us now discuss how the travel times are determined. Every, say, N simulation steps some virtual vehicles are inserted into the network and their progress through the network is tracked at every simulation step. More specifically, for each virtual vehicle ζ the following information is tracked during the simulation:

1) The route the vehicle is going to travel.
2) The link and the segment in which the vehicle currently is, and its position s in this segment.
3) The travel time that the vehicle has seen on the DRGIS panels it has already passed.
4) The realized travel time τ of the vehicle from the DRGIS panels it has already passed to the current position.
5) Whether or not the vehicle has left the network, and, if applicable, the time the vehicle left the network.

In order to track the position of the vehicles and to record the travel times, the METANET model has to be expanded as follows. Based on the METANET model equations given in Section II-A we can determine the time-dependent speed profile for all routes of a given network. Then the current position $s_{\zeta,m,i}(k)$ of vehicle ζ in segment i of link m is updated as follows:

$$s_{\zeta,m,i}(k+1) = s_{\zeta,m,i}(k) + v_{m,i}(k)T,$$

where $v_{m,i}(k)$ is the mean speed on segment i of link m at simulation step k. If the updated position $s_{\zeta,m,i}(k+1)$ is larger than the length L_m of segment i of link m, we put the vehicle ζ in the next segment of its route (say, segment i' of link m'), and we adapt the (new) position $s_{\zeta,m',i'}(k+1)$ accordingly. The travel time $\tau_{\zeta,\eta}(k)$ of vehicle ζ from DRGIS panel η to its current position is updated as follows:

$$\tau_{\zeta,\eta}(k+1) = \tau_{\zeta,\eta}(k) + T \quad .$$

III. Model Predictive Control

Remark: As the simulation time step T (typically 10 s) is usually different from the controller sample step T_{ctrl} (typically 1–5 min), we use different counters for the simulation (counter k) and for the control (counter z). If we assume for the sake of simplicity that T_{ctrl} is an integer multiple of T, the relation between the counters k and z at time instant $t = kT = zT_{\text{ctrl}}$ is $k = \frac{T_{\text{ctrl}}}{T} z$.

A. Approach

MPC [3] is an on-line model-based predictive control design strategy that has its roots in the process industry. A main advantage of MPC is that process and control constraints can be included in the control design. Thinking in terms of traffic control, constraints can be the minimal or maximal allowed on-ramp flow, maximal traffic signal cycle times, maximum queue lengths, etc.

In MPC at a given time $t = zT_{\text{ctrl}}$ the future process responses (outputs) are predicted by a model-based estimator over a prediction period $[t, t + N_{\text{p}}T_{\text{ctrl}})$, where N_{p} is the prediction horizon. MPC uses (numerical) optimization to determine the control sequence $u(z), \ldots, u(z + N_{\text{p}} - 1)$ that optimizes the predicted outputs in the sense of meeting a future target and/or satisfying constraints on the controlled and manipulated variables. In conventional MPC the aim is to reduce the tracking error, i.e., to reduce the difference between the actual system output and a predefined output trajectory. However, in the traffic control context the reference trajectory is not present, and for the performance indicator that has to be minimized we choose a weighted combination of the TTS, the prediction error, and the control variance (cf. (5) below).

In order to reduce the number of variables to be optimized and to obtain smoother signals, a control horizon N_{c} ($\leq N_{\text{p}}$) is defined in MPC, and the control signal is taken to be constant once the control horizon has passed $u(z+l) = u(z+N_{\text{c}} - 1)$ for $l = N_{\text{c}}, \ldots, N_{\text{p}} - 1$.

In order to be able to deal with disturbances, model errors, and changes in the system parameters, MPC uses a receding horizon approach, which operates as follows:

1) At the current time $t = zT_{\text{ctrl}}$ we measure or estimate (using, e.g., an extended Kalman filter) the current traffic state[1] of the network.
2) We solve the MPC control problem to obtain the estimated optimal control[2] sequence $u(z), \ldots, u(z+N_{\text{c}} - 1)$.
3) We apply the first sample element $u(z)$ of the control sequence to the system.
4) At the next controller sampling time step we set $z := z+1$, and we repeat the process starting from Step 1.

For the tuning parameters N_{p} and N_{c} we can use the following rules of thumb. The prediction horizon N_{p} must be chosen such that a vehicle can travel through the whole considered traffic network within the prediction period. This means that the route with the largest travel time in the worst case scenario (i.e., under congestion) must be considered when choosing the prediction horizon. The control horizon N_{c} must be tuned to realize an optimal performance at low computational cost.

[1]I.e.,the partial densities for every segment and reachable destination of a link, the mean speed of every segment of every link, and the partial queues at every origin.

[2]The control vector consists of the independent travel times at bifurcation nodes where dynamic route guidance is provided, and the ramp metering rates.

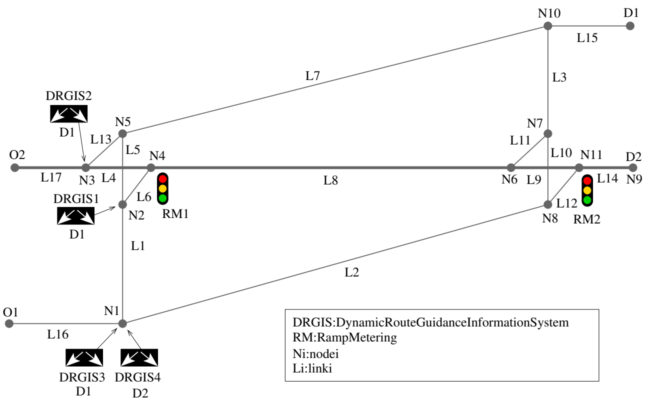

Fig. 1. The traffic network of the case study.

B. Objective function

We have selected the following objective function over the period $[zT_{\text{ctrl}}, (z + N_{\text{p}})T_{\text{ctrl}})$ (note, however, that the approach we propose works equally well for other performance indicators):

$$
\begin{aligned}
J(z) = {} & \xi_1 \alpha_1 \sum_{k \in \Omega(z)} \left[T \sum_{m \in \mathscr{L}} \sum_{i \in \mathscr{S}_m} \rho_{m,i}(k) L_m \lambda_m + \gamma T \sum_{o \in \mathscr{O}} w_o(k) \right] \\
& + \xi_2 \alpha_2 \sum_{\zeta \in \mathscr{V}(z)} \sum_{\eta \in \mathscr{D}(\zeta)} (\vartheta_{\text{pred}}(\zeta, \eta)) - \vartheta_{\text{real}}(\zeta, \eta))^2 \\
& + \xi_3 \alpha_3 \sum_{\ell = z}^{z+N_{\text{c}}-1} \| u(\ell) - u(\ell - 1) \|^2 \ ,
\end{aligned}
\tag{5}
$$

where $\Omega(z) = \left\{ k_0, k_0 + 1, \ldots, k_0 + N_{\text{p}} \frac{T_{\text{ctrl}}}{T} - 1 \right\}$ with $k_0 = z \dfrac{T_{\text{ctrl}}}{T}$, $\mathscr{L}$ is the set of indices of all links in the network, $\mathscr{S}_m$ is the set of indices of the segments of links m, $\mathscr{O}$ is the set of all origins, $\mathscr{V}(z)$ is the set of indices of all vehicles that left the network in the period $[zT_{\text{ctrl}}, (z+N_{\text{p}})T_{\text{ctrl}})$, $\mathscr{D}(\zeta)$ is the set of indices of DRGIS panels that vehicle ζ has encountered, variable $\vartheta_{\text{pred}}(\zeta, \eta)$ is the travel time shown on the DRGIS η for vehicle ζ, and $\vartheta_{\text{real}}(\zeta, \eta)$ is the actually realized travel time for vehicle ζ from DRGIS η to its destination.

The first term in J is the total time spent (both on the freeways and the on-ramp queues, where the relative contribution of the latter is determined by the weighting factor γ), the second term is the prediction error, and the third the control variance. The α_i's are normalization factors, and the ξ_i's are weighting factors for the different terms of the objective function. The values for the ξ_i's depend on the traffic policy imposed by the road administrator.

IV. Case Study

A. Set-up

The case study network is shown in Fig. 1, and consists of two origins O_1, O_2 and two destinations D_1, D_2. Origin O_2 and destination D_2 are on the freeway (which consists of links L_{17}, L_4, L_8, L_9 and L_{14}), whereas O_1 and D_1 are on the secondary road network (the other links).

Only one direction is considered, viz. from O_1, O_2 to D_1, D_2. For several origin-destination pairs, drivers can choose whether they travel via the freeway or via the secondary roads. There are three alternative routes from O_1 to D_1, two alternatives from O_1 to D_2 and from O_2 to D_1, and one way to travel from O_2 to D_2. At the bifurcation nodes N_1, N_2, and node N_3 DRGIS are installed that show the travel times to the destinations D_1 or D_2 via the several possible alternative routes.

The on/off-ramps are situated at points where the secondary road crosses the freeway. At each on-ramp a ramp metering system is installed.

B. Scenario and parameters

We consider the following scenario. At the start of the simulation we have a capacity reduction at destination D_2, which results in a shock wave originating at D_2 and going downstream until the downstream end of freeway link L_8 is congested. Calculations show that in this case the alternative routes from origin O_1 to destination D_1 get faster, resulting in more traffic choosing the alternative routes. The simulation starts from a steady state situation with the following flows or demands: 600 veh/h for the origin-destination pair (O_1,D_1), 1400 veh/h for (O_1,D_2), 900 veh/h for (O_2,D_1) , and 2100 veh/h for (O_2,D_2). However, 5 min after the simulation has started, the total demand at O_2 increases, resulting in a flow of 1200 veh/h for (O_2,D_1), and 2800 veh/h for (O_2,D_2).

The METANET parameters used for the simulation of the case study network are based on the METANET validation as described in [12] with some adjustments. More specifically, in our case study two values for ν are defined as is also done in [6], [7]. In case the downstream density is lower than the density on the present link, then we select $\nu = \nu_{\text{low}} = 35\,\text{km}^2/\text{h}$, and else $\nu = \nu_{\text{high}} = 60\,\text{km}^2/\text{h}$. The capacity of the freeway links is chosen as 2200 veh/h, and the capacity of the secondary road links is chosen as 1500 veh/h. The free flow speed $v_{\text{f},m}$ is 120 km/h for freeway links, and 80 km/h for secondary road links. Furthermore, we have $\tau = 20\,\text{s}$, $\rho_{\max} = 180$ veh/km/lane, $\kappa = 40$ veh/km, and $v_{\min} = 7$ km/h as the minimum speed (cf. [12]).

For the controller we have taken $T_{\text{ctrl}} = 5$ min. The prediction horizon $N_{\text{p}} = 12$ corresponds to a prediction of 1 h ahead. For the control horizon we take $N_{\text{c}} = 9$, which corresponds to a period of 45 min, which is shorter than the prediction horizon, but long enough to get a good performance. The weighting parameters were all set to 1.

C. Simulation results

We have simulated the network of the case study both with and without MPC control. Below we discuss some of the most relevant results of these simulations.

Fig. 2 shows the evolution of the speed on the freeway link L_8 when no control measures are active. This link is the main part of the freeway, and it is also used by traffic that is destined to secondary road destinations. Due to the shock wave entering via destination D_2 at the beginning of the simulation period, the speeds on the freeway are reduced drastically. Since drivers are not informed about the alternative routes, which could reduce their travel times, they still choose to travel via link L_8 because they have no information about the queue. The lack of information drivers receive when there is no DRGIS active results in the inefficient use of some secondary road links, such as link L_{10}. Although link L_{10} can be optimally used for the rerouting of traffic flow, the link is almost unused in the uncontrolled case.

When the DRGIS is activated and MPC is applied, we get an improvement in the mean speed over the freeway as is shown in Fig. 3. The freeway is relieved from congestion because of the rerouting due to the DRGIS, which results in more traffic choosing for alternative routes via the secondary roads. This leads to less traffic on link L_8 and increased speeds with respect to the no-control case. Furthermore, the ramp metering reduces the inflow of traffic destined to the freeway destination and thereby improves the throughput on the freeway. As a consequence, the shock wave is damped significantly.

The evolution of the flows in link L_{14} in the uncontrolled and the controlled case is represented in Fig. 4 and 5. In the uncontrolled case, the flow as well as the speeds on this link are reduced drastically due to the shock wave the flow. The outflow of the network is reduced due to the shock wave, which results in congestion and lower speeds in the rest of the network. When DRGIS and ramp metering are activated the flow on link L_{14} improves significantly. As the effect of the shock wave is reduced by the rerouting and ramp metering, the outflow from the network also increases.

The TTS with MPC control active is 4530.6 veh.h compared 6365.4 veh.h in the no control case, which corresponds to an improvement of 28.8 %.

V. Conclusions and future research

We have considered the problem of integrated Model Predictive Control (MPC) traffic control with ramp metering and Dynamic Route Guidance Information Systems (DRGIS) as the traffic control measures (but note that additional control measures such as, e.g., variable speed limits, can easily be included in the proposed approach). In the integrated traffic control approach the DRGIS is used as an information provider to the drivers, and ramp metering as a control tool to redistribute the delays over the on-ramp and the freeway. This results a control strategy that, on the one hand, reduces the total time spent in the network by optimally rerouting traffic over the available alternative routes in the network, but, on the other hand, also keeps the difference between the travel times shown on the DRIPs and the travel times actually realized by the drivers as small as possible. The simulations done for the case study show that rerouting of traffic and on-ramp metering using MPC may lead to a significant improvement in performance.

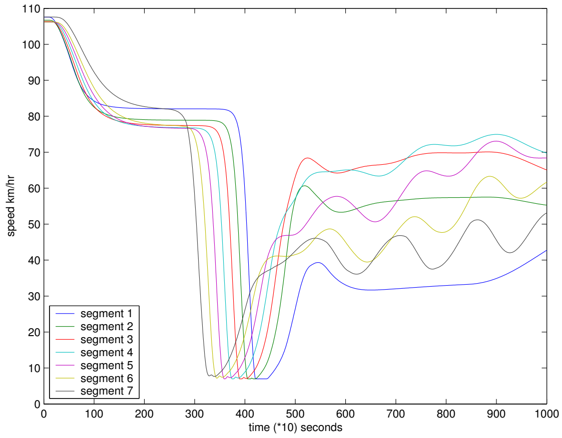

Fig. 2. Evolution of the mean speed on the segments of link L_8 in the no-control case.

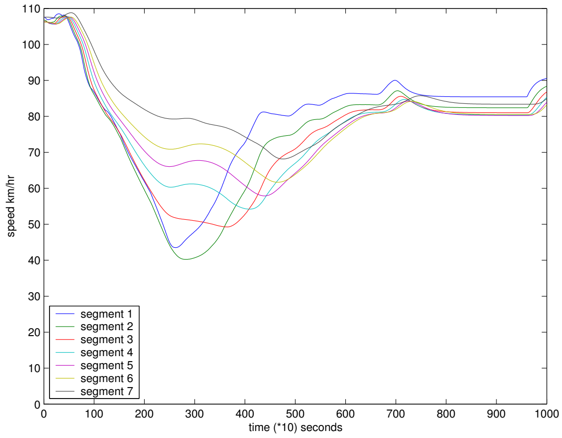

Fig. 3. Evolution of the mean speed on the segments of link L_8 when integrated MPC control is applied.

Topics for future research are: investigation of other networks and scenarios; using other prediction and simulation models; comparison of the performance of the integrated MPC approach with that of other traffic control strategies; and integration of additional traffic control measures.

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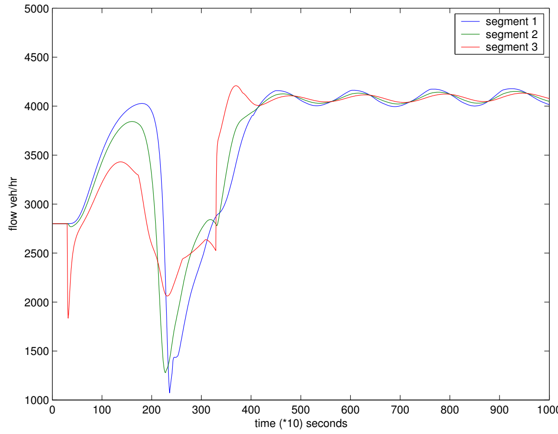

Fig. 4. Evolution of the flow on the segments of link L_{14} in the no-control case.

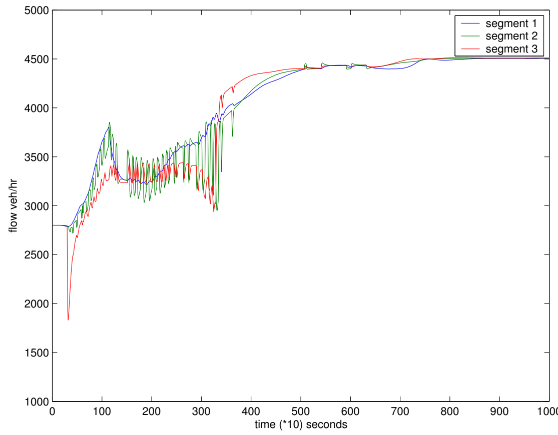

Fig. 5. Evolution of the flow on the segments of link L_{14} in the controlled case.

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