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Integrated Model Predictive Control of Dynamic Route Guidance Information Systems and Ramp Metering

A. Karimi, A. Hegyi, B. De Schutter, J. Hellendoorn, F. Middelham

Abstract— **We propose an integrated approach for dynamic route guidance and ramp metering control using Model Predictive Control (MPC). The main control objective is to minimize the total time spent in the network by giving accurate travel times as controller input to the network while taking into account the effect of other traffic control measures, such as ramp metering. The travel times shown on the dynamic route guidance panels allow the drivers to make a choice based on possible alternatives. By aiming at minimizing the total time spent as well as the difference between travel times shown to the drivers and the travel times 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 total time spent while the drivers get accurate travel time information.**

I. Introduction and problem description

Dynamic traffic management aims at increasing the safety and efficiency of the existing traffic networks using dynamic traffic management measures such as ramp metering systems, Dynamic Route Guidance Information Systems (DRGIS), variable speed limits, lane closures, shoulder lane opening, tidal flow, 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. Ramp metering can be used to spread the demand from the on-ramp in time, and to reduce the inflow from the on-ramp. This should result in less congestion on the freeway. Another strategy is to use ramp metering for redistributing the delay between freeway and on-ramp. DRGIS panels can be 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 traffic control field 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, we introduce and use *optimized* travel times, which are optimized in combination with and at the same time as the other control signals.

The combination of on-ramp metering and dynamic route guidance with the use of an optimal control strategy has been considered 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, it is rather hard to find those traffic control measures that realize the optimal splitting rates.

In this paper we propose a network-wide control strategy based on the integration of DRGIS and ramp metering with the use of the Model Predictive Control (MPC) [3], [4]. MPC is a control algorithm that searches for the optimal future control sequence that minimizes a predefined objective function over a near-future time horizon. We 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 road into account. The control signals we consider are ramp metering rates and travel times shown on the DRGIS panels. Usually these signals are determined separately using different objective functions, decomposition, or hierarchical optimization. However, we 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 panels and the ramp metering rates are optimized to minimize the objective function, which consists in minimizing the total time spent on the one hand, and in reducing the difference between the travel times

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shown on the DRGIS panels and the actually realized travel times. Hence, the drivers will be guaranteed a minimal but accurate travel time. Being given accurate travel times drivers will get more confidence in the DRGIS information, resulting in a higher compliance rate in the future.

The MPC approach for integrated of route guidance and ramp metering control 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. In Section II we describe the models we use to describe the behavior of the traffic flows and the reaction of the drivers to the route guidance. Next, we present the integrated MPC traffic control approach in Section III, and finally we illustrate our approach for a case study in Section IV.

II. Prediction model

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 [5], [6] is a macroscopic traffic flow modeling and simulation tool. As we consider (re)routing of traffic, we will use the destination-oriented METANET model. We will only present the basic ideas behind this model below. For a more detailed explanation we refer to [5], [6].

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 locations 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 T typically has a value of about 10 s). For each segment i of each link m we define the following macroscopic variables, which are used to describe the state of the traffic network for simulation step k:

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

The METANET model describes the evolution of the traffic flows using update equations for $\rho_{m,i}(k)$ (based on the conservation of vehicles) and $v_{m,i}(k)$ (based on relaxation, convection, and anticipation effects), and using the relation $q_{m,i}(k) = \rho_{m,i}(k)v_{m,i}(k)\lambda_m$. In case a link is an on-ramp the model includes the queue length $w_o(k)$ at the given on-ramp o at time $t = kT$, which — if applicable — also depends on the ramp metering rate $r_o(k)$. We refer to [5], [6] for the exact equations.

In the destination-oriented METANET model $\gamma_{m,i,j}(k)$ denotes the fraction of the traffic in segment i of link m that is going to destination j at time $t = kT$. In a bifurcation node n with two or outgoing links, the fraction of the incoming flow at time $t = kT$ going to destination j traveling via outgoing link m is denoted by $\beta^m_{n,j}(k)$. In the basic METANET model, this fraction is an external input. However, in our case, it will be part of the prediction model.

B. Driver route choice modeling

One of the variables in the METANET 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 [7]–[9], 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. Also in traffic modeling these kinds of models are used. Consumers are then the drivers, and the cost is the comfort, safety, or travel time of the possible alternative routes to reach 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. For the calculation of the split rates out of the travel time difference between two alternatives the logit model results in

$$\beta^m_{n,j}(k) = \frac{\exp(\sigma\,\vartheta^m_{n,j}(k))}{\exp(\sigma\,\vartheta^{m_1}_{n,j}(k)) + \exp(\sigma\,\vartheta^{m_2}_{n,j}(k))}$$

for $m = m_1$ or $m = m_2$, where $\vartheta^m_{n,j}(k)$ 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 [10], 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 expression (1) below).

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 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

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

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

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

III. Model Predictive Control (MPC)

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. MPC approach to traffic control

MPC [3], [4] 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 total time spent, the prediction error, and the control variance (cf. equation (1) 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 the current traffic state of the network.
2) We solve the MPC control problem to obtain the estimated optimal control 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 (with a re-estimation of the model parameters every, say, M steps if necessary).

The essential tuning parameters for MPC are the prediction horizon N_{p} and the control horizon N_{c}, for which we can use the following rules of thumb in order to determine appropriate values. 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.

B. States, control signals, and objective function

The state vector of the traffic network consists of 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. The control vector consists of the independent travel times at bifurcation nodes where dynamic route guidance is provided, and the ramp metering rates. The process disturbance or external input vector consists of the demands, composition rates at the origin links, the splitting rates at bifurcations without guidance, and the drivers' compliance rates to guidance recommendations.

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

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

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

The first term in the objective function (1) is the total time spent (both on the freeways and in 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 parameters α_i 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 typically depend on the traffic policy imposed by the road administrator.

IV. CASE STUDY

A. Set-up

The case study network is shown in Figure 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 (which consists of the other links). Each link consists of one or more segments of 1 km except for the on-ramp links (L_6,L_{12}), which have a length of 700 m. Only one direction is considered, and that is from O_1, O_2 to D_1, D_2 (bottom-up and left-right in the figure). So all links can be considered to be unidirectional.

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. DRGIS are installed at the bifurcation nodes N_1, N_2, and node N_3 as follows:

- At node N_1 two DRGIS are installed, one for destination D_1 and one for destination D_2. The DRGIS for destination D_1 shows three travel times because there are three alternative routes from node $N1$ to destination D_1: L_1–L_6–L_8–L_{11}–L_3–L_{15}, L_1–L_5–L_7–L_{15}, and L_2–L_{10}–L_3–L_{15}. The DRGIS at node N_1 for destination D_2 shows two travel times: for routes L_1–L_6–L_8–L_9–L_{14} and L_2–L_{12}–L_{14}.
- At node N_2 there is only one way to travel to destination D_2, and there are two alternatives to travel to destination D_1: L_6–L_8–L_{11}–L_3–L_{15} and L_5–L_7–L_{15}.
- At node N_3 there is only one alternative to travel to destination D_2, and there are two alternatives to travel to destination D_1: L_{13}–L_7–L_{15} and L_4–L_8–L_{11}–L_3–L_{15}.

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. Traffic from a secondary road that wants to travel via freeway has to cross one of the two on-ramps. Traffic from the freeway that wants to travel to destination D_1 has to cross one of the off-ramps.

B. Scenario

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. The shock wave goes 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 these alternative routes. The simulation starts from a steady state situation in which we have 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).

C. Model and controller parameters

The METANET parameters used for the simulation and prediction of the case study network are based on the METANET validation as described in [11] with some adjustments (cf. [12]–[14]). The capacity of the freeway links is chosen as 2200 veh/h, and the capacity of the secondary road links as 1500 veh/h. The free flow speed is 120 km/h for freeway links, and 80 km/h for secondary road links.

For the controller we have taken $T_\mathrm{ctrl} = 5$ min. The prediction horizon $N_\mathrm{p} = 12$ corresponds to a prediction of 1 h ahead. For the control horizon we take $N_\mathrm{c} = 9$, 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 chosen as 1, except for the weighting parameter ξ_2 of the prediction error, for which we have simulated both $\xi_2 = 0$ and $\xi_2 = 1$ in order to determine the effect of the prediction error.

V. SIMULATION RESULTS

We have simulated the network of the case study for the scenario given above both with and without MPC control. Below we discuss some of the most relevant results.

Figure 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

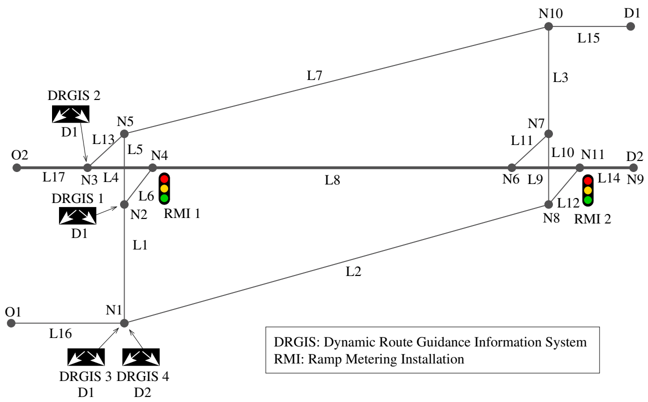

Fig. 1. The traffic network of the case study consists of two origins O_1, O_2, and two destinations D_1, D_2. The network contains a freeway (consisting of links L_{17}, L_4, L_8, L_9, and L_{14}), and secondary roads (consisting of the other links). There are four DRGIS panels and two on-ramp metering installations.

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 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 L_{10}. Although 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 Figure 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 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 traffic from origin O_2 destined to D_1 is routed via L_{13}. Traffic from O_2 destined to D_2 has no alternative than to travel via the highway. Traffic that originates in O_1 and is destined to D_1 is routed via L_2, while traffic from O_1 destined to D_2 is routed via L_1. The traffic that is routed via L_1 to destination D_2 has to travel via the on-ramp link L_6. Although there is no critical situation on link L_8 the metering anticipates on the fact that if all traffic is admitted to the freeway this can cause the shock wave not to be reduced optimally. The metering admits at least 60 % of the traffic on on-ramp link L_6 to enter the freeway. The ramp metering causes queues on the on-ramp link L_6 to spill back to L_1, which results in a queue of 2 km on L_1.

The total time spent in case of no control is 6365.4 veh.h compared to 4530.6 veh.h in the case of MPC control, which corresponds to an improvement of 28.8 %.

Figure 4 shows the difference in prediction error between not taking the prediction error into account in the objective function ($\xi_2 = 0$) and taking the prediction error into account ($\xi_2 = 1$). The travel times shown on the DRGIS and the metering rates are optimized in both cases. Each dot in Figure 4 represents one vehicle that left the network. The optimal reference shown in the figure corresponds the optimized travel times shown on the DRGIS being equal to the travel times realized by the drivers. The angles α^+ and α^- are representative for the maximum errors in case the optimized travel times were too low and too high respectively. Interesting is the fact that the optimized travel times are, in most cases, higher than the realized travel times. This is a subject of future research.

VI. 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 can easily be included in the proposed approach). In the proposed approach the DRGIS is used as an information provider to the drivers, and ramp metering as a control tool to redistribute delay over the on-ramp and the freeway. The travel times shown on the DRGIS are optimized travel times, which are chosen such that the reactions of the drivers and the control actions of ramp metering are taken into account. This results in one optimization that optimizes both the ramp metering and the DRGIS travel times at the same time such that on the hand the total time spent in the network is reduced by optimally rerouting traffic over the available alternative routes in the network, but on the other hand the difference between the travel times shown on the DRGIS system and the realized travel times is also kept as small as possible. The approach was illustrated for a simple case study, for which the integrated rerouting and ramp metering approach using MPC leads to an improvement in performance of 28.8 % for the case study.

Some topics for future research are: investigation of other networks and scenarios; using other traffic prediction and simulation models; determination of optimal values for the controller parameters; comparison of the performance of the integrated MPC approach with that of other control strategies such as ALINEA ramp metering [15] combined with DRGIS systems showing instantaneous or predicted travel times; and integration of more traffic control measures.

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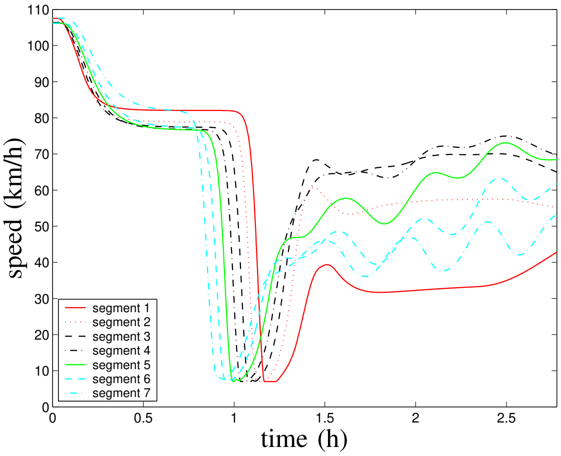

Fig. 2. Evolution of the mean speed on the segments of link L_8 in the no-control case. When no control measures are activated, the mean speed on link L_8 decreases drastically, resulting in congestion.

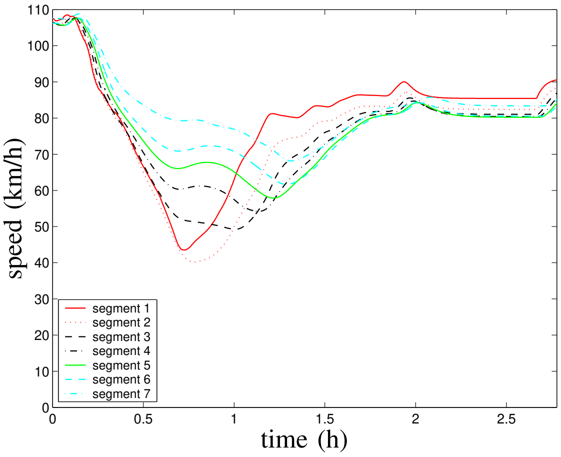

Fig. 3. Evolution of the mean speed on the segments of link L_8 when integrated MPC control is applied. The rerouting results in more traffic choosing for alternative routes via the secondary roads, which leads to less traffic on L_8 and increased speeds with respect to the no-control case.

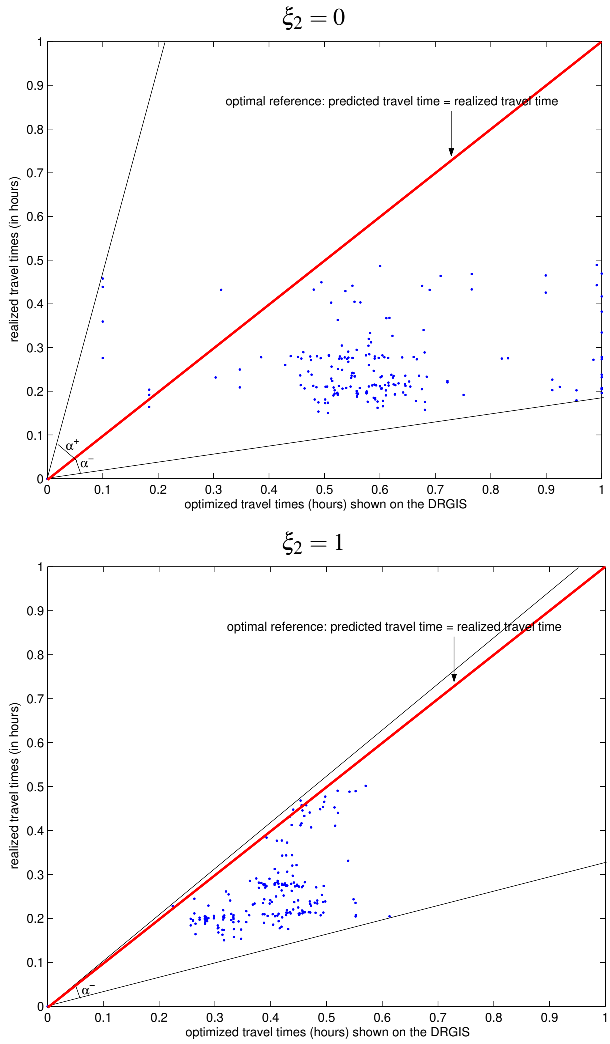

Fig. 4. Plot of the travel time prediction error in case the weighting factor ξ_2 for the prediction error term in the objective function is set to 0 (top) and to 1 (bottom). The angles α^+ and α^- are representative for the maximum errors in case the optimized travel times were too low and too high respectively.

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