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Information providing as a control measure in an integrated traffic control approach

M. van den Berg, B. De Schutter, J. Hellendoorn

Abstract— **We develop a control method for traffic networks that uses information providing as a control measure. The provided information consists of travel time information of different possible routes, shown on variable message signs. We will present a model that describes the change in turning rates due to a travel time difference between two possible routes.**

The controller we develop integrates the provided information with variable speed limits, ramp metering, or other control measures. This makes it possible to influence the turning rates and slow down the traffic in such a way that the performance of the network is optimal, without displaying predicted travel times that differ too much from the experienced travel times.

We consider a simple case study for which we first illustrate the effects of the route choice model without any control in a first simulation. Next, we illustrate the effect of variable speed limits in the proposed setting when they are used for incident detection and warning, and when they are used in an integrated control method together with the travel time information.

I. Introduction

Congestion in traffic networks currently forms a major problem. It can be solved by creating new roads, or by making better use of the existing infrastructure. In this paper we consider the second option. To improve the capacity of the existing infrastructure there exist different control measures. There are 'hard measures' like traffic signals [1], speed limits [2], [3], and ramp metering signals [4], which the drivers have to obey. On the other hand, there are also 'soft measures', to which the driver can comply or choose not to do so. Providing information is such a 'soft measure'.

In this paper we will show that although drivers are not forced to react on the information, providing this information can nevertheless be an effective measure to improve the network performance, especially when it is integrated with other available hard control measures. Providing information can have two goals: informing the drivers about what they can expect, and trying to influence the route choice of the drivers. We target the second goal, i.e. we want to influence the route choice to change the way the traffic flows divide themselves over the network, i.e. the traffic assignment.

In a network with different routes between a specific origin and destination, the route drivers select can depend on the drivers' knowledge of the network, their previously experienced travel times, their habits, their preference for freeways, the nice surroundings, etc. The first paper that describes the effects concerning route choice is [5]. Other papers on this topic are [6], [7], which describe the reasoning of the drivers while selecting their route, and which notice that the route choice will lead to a so called user equilibrium traffic assignment. This is the assignment in which all routes have the same costs for the drivers. Several authors have developed methods to compute this static equilibrium assignment [8], [9]. But with varying demands the equilibrium assignment will also vary, and so dynamic traffic assignment algorithms have been developed [10], [11].

Currently many control measures and information systems change the traffic assignment, disturbing the equilibrium assignment. As a result, the motives of the drivers to select a specific route get more attention [12], [13]. When the drivers motives are known, their decisions can be influenced by e.g. advanced traveler information systems [14], [15]. When we want to use these systems to influence the traffic assignment, it should be taken into account that the information provided only changes the route choice of the drivers when it differs enough from the knowledge the drivers have based on previous experiences. The amount of influence will also depend on the reliability of the provided information; the difference between the given information and the experienced travel times may not have been too large in the past.

Nowadays traffic management bodies start to explore the possibilities of changing the traffic assignment by influencing the route choice of the drivers [16] via providing information. The traffic management bodies define e.g. preferred routes towards special destinations like the city center, a main business building, or recreational areas. Drivers with these destinations are thus kept out of residential and/or industrial areas, resulting in a traffic assignment that is desired by the traffic management bodies.

The information is often provided via Variable Message Signs (VMS). The effect of VMS information is described in [17], [18]. Which information should be given is also a subject of research and is discussed in e.g. [13]. Some authors use information on VMS to control the traffic [19], [18].

In this paper we will use VMS in combination with speed limits to influence the route choice of the drivers, in order to make them select their routes approximately according to the desired traffic assignment. Note however that other traffic control measures can also be used with the control method we will develop. For the integrated control of the VMS and the speed limits, we will use model predictive control (MPC). MPC [20], [21] has been applied successfully to coordinated control of freeway networks [3], [22]. MPC is an on-line method that uses a model to predict the behavior

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of the traffic for a specific period. With this prediction the settings for the control measures that lead to the best network performance during this period are determined via optimization, and applied using a moving horizon approach.

This paper is organized as follows. We describe the traffic flow model and the implementation of the speed limits in Section II. In Section III an example of a possible a route choice model is explained, and Section IV describes how drivers react on information. The integrated control structure which uses MPC is proposed in Section V. To illustrate the method a case study is done in Section VI.

II. Traffic flow model and speed limits

MPC uses a model to predict the traffic. This model should give an accurate description of the traffic flows, but it should not be too computationally intensive. Thus we propose to use a macroscopic traffic flow model. As an example we will use the METANET model, developed by Messmer and Papageorgiou [23]. The reaction on the speed limits is formulated as in [3].

Our short description of the METANET model is based on [22]. The freeway network is described as a set of links, connected by nodes. The freeway links are divided into segments, and the state of the freeway network at time $t = kT_{\text{sim}}$ (where T_{sim} is the simulation time step) is characterized by the mean density $\rho_{m,i}(k)$, flow $q_{m,i}(k)$ and speed $v_{m,i}(k)$ for each segment i of freeway link m.

At nodes the arriving flows are added together, and the resulting total flow is divided over the leaving nodes according to the turning rates:

$$q_{m,0}(k) = \beta_{n,m}(k) Q_{\text{tot},n}(k) \quad \text{for each} \quad m \in O_n \qquad (1)$$

where $Q_{\text{tot},n}$ is the total flow entering node n, $\beta_{n,m}(k)$ is the turning rate from node n to leaving link m, and O_n the set of leaving links of node n.

The reaction on the speed limits is modeled by changing the desired speed of the drivers [3]:

$$V(\rho_{m,i}(k)) = \min[V_{\text{desired}}(\rho_{m,i}(k)), (1+\alpha) v_{m,\text{control}}(k)]$$

where $V(\rho_{m,i}(k))$ is the desired speed for a given density $\rho_{m,i}(k)$ when speed limits are active, $V_{\text{desired}}(\rho_{m,i}(k))$ is the desired speed without speed limits, $v_{m,\text{control}}$ the applied speed limit, and α a compliance factor that expresses to which extent the speed limits are obeyed. The value of α can change depending on the kind of drivers on the road or depending on the level of enforcement.

III. Route choice model

When there are different routes between an origin and destination drivers will select one of these routes. This is modeled with a route choice model that describes the route choice behavior of drivers based on given or measured variables. To be able to use a route choice model in the MPC structure there are some requirements for the model. First we will explain the requirements, and next we give a description of the model we use for our control approach.

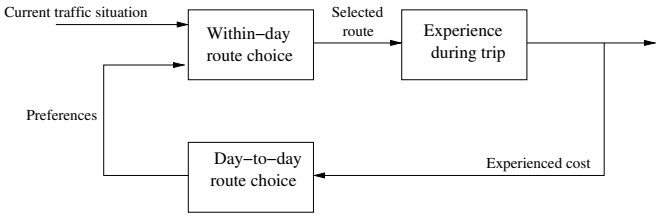

Fig. 1. Overview of the route choice process

A. Requirements for the route choice model

There exist two kinds of route choice mechanisms. There is the day-to-day change in route choice, and the within-day route choice. Both mechanisms must be taken into account when we want to influence route choice by providing information [24]. The most important requirements for the route choice model are that it should describe both mechanisms, using measurable variables. The day-to-day model may contain some parameters for preferences, e.g. nice surroundings, no traffic signals, wider lanes. The updating of the model at the end of each day should be done based on measurable results of the last day, e.g. queue lengths, travel times, delays, etc.

The within-day model has to describe a relation between the route choice and the measurable quantities at the moment the driver has to make this route choice. This quantities are e.g. the instantaneous travel time, instantaneous queue lengths, or even better the flow, density or speed at this moment. An overview of the resulting route choice process is given in Figure 1.

We could select one of the models described in [12], [13]. However, these models are complex and detailed, and as a result, they require too much computational effort to be used as a prediction model for the controller. Nevertheless, they can be used as simulation models. As prediction model we use a model based on statistical learning, which will be described next.

B. Statistical learning model

We assume that the within-day route choice process of a driver is divided into three steps:

1) First the driver analyzes the current situation. For the sake of simplicity of the exposition we will from now on assume that the driver makes his decisions based on one important variable only, e.g. the density. However, the approach can easily be generalized to the case where several variables determine the decision. We divide all possible densities in, say, three groups: low, medium and high density. The driver selects to which group the current density belongs.
2) In the second step the driver estimates which route will result in the lowest costs, based on the current density. For the sake of simplicity we assume that the only factor that influences these costs is the travel time, but note that the extension to more factors is straightforward. This means that the driver will select

the route that according to his beliefs has the shortest travel time.

3) During the last step, the driver decides whether he will indeed take the route with the lowest cost, or, e.g. when two routes have the same cost, which route is the best one to select.

The main decisions in the within-day route choice process are based on the knowledge of the driver. This knowledge is described with the day-to-day route choice model, which is updated after each trip. The day-to-day route choice model contains estimated travel times, and the probabilities that drivers select a route.

1) Estimated travel times: For each density group, the estimated travel time of each route is determined. These estimated travel times are computed by taking the average of previously experienced travel times, using a forgetting factor because the last experiences are seen as more important according to [13]. So we have

$$M_{\text{est,new}} = \omega M_{\text{last exp}} + (1-\omega) M_{\text{est,prev}}$$

where $M_{\text{est,new}}$ is the new estimate of the travel time, $M_{\text{est,prev}}$ is the previous estimate, $\omega \in [0,1]$ is the multiplication factor , and $M_{\text{last exp}}$ is the last experienced travel time.

2) Probability of selecting a route: The probability that a driver selects a specific route for a given density is based on earlier experiences. To compute this probability statistical information of previous trips is used. Note that we aggregate the knowledge of the drivers assuming that historical experiences can be accumulated. We will illustrate the procedure with a situation where two route choices are possible. The probability of selecting route 1 under low density conditions, $P(S1|low)$ is computed as:

$$\begin{aligned} P(S1|low) =& P(S1|R1)P(R1|low) \\ &+ P(S1|R2)P(R2|low) \\ &+ P(S1|EQ)P(EQ|low) \end{aligned} \tag{2}$$

The first term describes the probability that route 1 is the shortest under low density conditions times ($P(R1|low)$) times the probability that route 1 is selected when route 1 is the shortest ($P(S1|R1)$). The second term describes the probability that route 1 is selected when route 2 is the shortest given low density conditions. The last term expresses the probability that route 1 is selected when the routes are equally long. Because the probability that both routes are equally long is also included, the model does not tend to a route choice of fifty-fifty for each route when the travel times are equal, but maintains the route choice ratio that has resulted in the equal travel times.

The probabilities are computed as follows:

$$P(R1|low) = \frac{R1_low}{R1_low + R2_low + EQ_low}$$

$$P(S1|EQ) = \frac{S1_EQ}{S1_EQ + S2_EQ}$$

where $R1_low$, $R2_low$, EQ_low, $S1_EQ$, and $S2_EQ$ are counters that express how often these combinations have happened during earlier trips. Other probabilities are computed in the same way. The counters are updated after each trip. When updating them, a forgetting factor is used to describe the effect that last experiences are more important.

Because the prediction model is macroscopic, we use this probability as the percentage of the traffic that selects a route. This gives for the turning rates towards route 1 on node n under low density conditions:

$$\beta_{n,1}^{\text{routechoice},low}(k) = P(S1|low). \tag{3}$$

IV. Reaction on information

We model the reaction on information separately from the route choice model. There are some arguments to include it in the learning route choice model, but to be able to clearly distinguish the effects of information and those of normal route choice, we formulate it separately.

To provide the information we use a VMS that shows travel times for the different routes. The reaction on the information is based on the presented difference in travel time between the routes, and on the number of drivers that can be influenced to change their route. We first model the reaction on a cost difference, and next the number of drivers that can be influenced by the information is described.

A. Reaction on a cost difference

The model developed by Dial [9] is used as a model to describe the likelihood that drivers will change their route based on the given information. The model computes the likelihood ($l_{r,p}$) that drivers with a preference for route r will change their preferred route into route p according to:

$$l_{r,p}(k) = \begin{cases} 1 - \exp(\theta(C_p(k) - C_r(k))) & \text{if } C_p(k) < C_r(k) \\ 0 & \text{otherwise} \end{cases}$$

where $C_p(k)$ is the cost of route p, $C_r(k)$ the cost of route r, and $\theta \in [0,1]$ represents the amount of traffic that can be influenced by the provided information. When θ is 1, all drivers can be influenced by the information, while when θ is 0, none of them can.

Returning to the example with two possible routes, the turning rate toward route 1 can be computed as:

$$\begin{aligned} \beta_{n,1}^{\text{information}}(k) =& \beta_{n,1}^{\text{routechoice}}(k) - l_{1,2}(k)\beta_{n,1}^{\text{routechoice}}(k) \\ &+ l_{2,1}(k)\beta_{n,2}^{\text{routechoice}}(k) \end{aligned} \tag{4}$$

where $\beta_{n,1}^{\text{information}}(k)$ is the turning rate toward route 1 based on information and route choice, $\beta_{n,1}^{\text{routechoice}}(k)$ and $\beta_{n,2}^{\text{routechoice}}(k)$ the turning rates toward route 1 and 2 resulting from (3). Note that this method is easily extended to networks with several possible routes.

As all route choice processes are included in the turning rate $\beta_{n,r}^{\text{information}}(k)$ we use this turning rate when predicting the traffic (see (1)), so $\beta_{n,m}(k) = \beta_{n,r}^{\text{information}}(k)$, assuming that freeway link m is a part of route r.

V. Integrated control

The control measures we describe in this paper are route information and speed limits. The effect of the measures can be increased by using them in an integrated control structure. We propose a model predictive control structure, and introduce the corresponding costs and control signals.

A. Model predictive control (MPC)

MPC works as follows [20], [21]. At a given time $t = k_{\mathrm{c}}T_{\mathrm{c}} = kT_{\mathrm{sim}}$ (where T_{c} is the controller time step) the MPC controller uses the prediction model (see Section II), the route choice model (see Section III), and numerical optimization to determine the optimal control sequence $c^*(k_{\mathrm{c}}), \ldots, c^*(k_{\mathrm{c}} + N_{\mathrm{p}} - 1)$ that minimizes a given performance indicator $J(k_{\mathrm{c}})$ over the time period $[k_{\mathrm{c}}T_{\mathrm{c}}, (k_{\mathrm{c}} + N_{\mathrm{p}})T_{\mathrm{c}})$ based on the current state of the traffic network and on the expected demands over this period, where N_{p} is called the prediction horizon. The prediction horizon should be long enough to show all the effects of a control action. This can be reached by choosing it larger than or equal to the time that is needed by a vehicle to drive through the longest route of the network.

Furthermore, a receding horizon approach is used in which at each control step only the first control input sample $c^*(k_{\mathrm{c}})$ is applied to the system during the period $[k_{\mathrm{c}}T_{\mathrm{c}}, (k_{\mathrm{c}}+1)T_{\mathrm{c}})$. For the next control time step the optimization procedure is started again.

B. Performance indicator and control signal

The MPC method uses a performance indicator to determine the performance of the network. As main performance indicator we will consider the total time spent (TTS) by all vehicles in network, but note that the proposed approach also works for other performance indicators.

In addition to the TTS, the total performance indicator contains two other factors. One of them is a penalty on variations in the control signals, preventing fast switching of the signals. To increase the reliability of the provided travel time information, a penalty on the difference between the shown travel time and the experienced travel time is also included in the performance indicator:

$$J(k_{\mathrm{c}}) = \mathrm{TTS}(k_{\mathrm{c}}) + \gamma_1 \Big(\mathrm{var}(c(k_{\mathrm{c}})) \Big) + \gamma_2 \sum_{r \in R} \Big| \mathrm{TT}_r(k_{\mathrm{c}}) - \mathrm{TT}_r^{\mathrm{info}}(k_{\mathrm{c}}) \Big|$$

where R is the set of possible routes, TT_r the real experienced travel time on route r, $\mathrm{TT}_r^{\mathrm{info}}$ the travel time shown on the VMS for route r, and γ_1, γ_2 are weighting factors.

The control signal consists of the values for the speed limits and the values for the travel times that should be shown on the VMS. The MPC method can handle hard constraints, and so minimum and maximum values for the speed limits can be taken into account. Also a maximum length for the queues at the origins can be guaranteed.

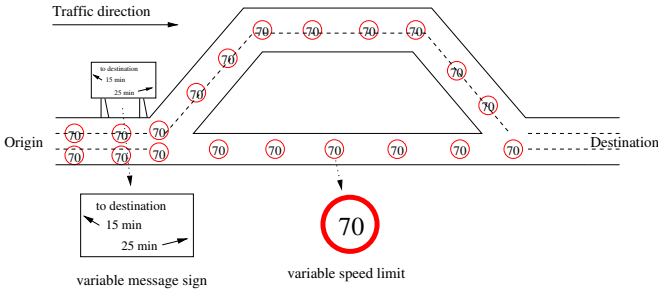

Fig. 2. Layout of the network

VI. Case study

We will use a simple case study to show the effects of the integrated MPC method. We have selected a network with two possible routes, see Figure 2. A three-lane freeway splits into a one-lane freeway and a two-lane freeway, where the two-lane freeway is longer than the one-lane freeway. Later the two freeways join each other again in a three-lane freeway. The shortest route with one lane is route 1, the longest route with two lanes is route 2. The VMS is located at the splitting node, and shows travel times for both routes. Speed limits can be applied on both routes.

The traffic scenario is chosen such that all three density groups appear, and that the highest density results in a congestion at the shortest route. The traffic demand varies in discrete steps from 2000 veh/h, to 4000 veh/h, to 8500 veh/h, and back to 4000 veh/h and 2000 veh/h. As traffic model we have used the METANET model, and for the route choice the model described in Section III. In this model the probability that the shortest route is also the best selection is very large, and so we assume this probability is one: $P(S1|R1) = 1$. In the same way we assume that selecting the longest route is not very likely, so we select $P(S2|R1) = 0$. With the assumed values, (2) can be simplified to:

$$P(S1|low) = P(R1|low) + P(S1|EQ)P(EQ|low)$$

For the MPC controller we have selected $N_{\mathrm{p}} = 10$ and $T_{\mathrm{c}} = 1$ minute. Because the day-to-day learning is also an important aspect of the model, each of the simulations is repeated 100 successive days.

The first simulation shows the performance of the route choice model. Figure 3 shows the development of the preferred turning rate toward route 1, for each of the three density groups, from day 1 to day 100. As starting value for all turning rates we have selected 0.5. The solid line represents the turning rates for low density situations. At low densities it is logical that the shorter but smaller route is the fastest, and indeed, the turning rate towards route 1 increases over the days. The dashed line represents the turning rate for medium density conditions. As the density on the shortest route has become a little higher, the travel time on this route is increased. Both routes have nearly the same travel time, resulting in a turning rate of 0.45. Finally, the dotted line shows the turning rates for high density conditions. Route

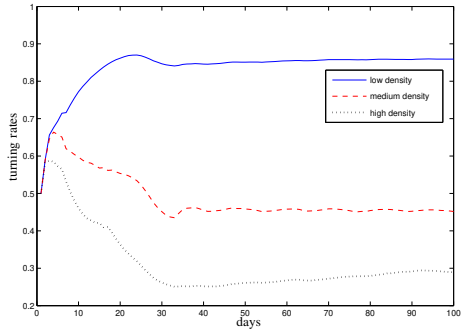

Fig. 3. Evolution of the turning rates toward route 1

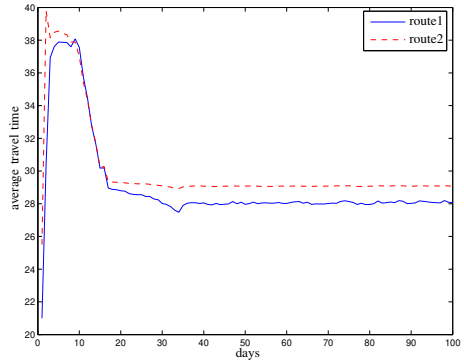

Fig. 4. Evolution of the average travel times

1 is congested, and so more drivers select the second route and the turning rate towards route 1 decreases.

Figure 4 shows the average travel time for each day. While the drivers are still learning, the travel times on both routes are high. After 17 days the drivers have selected the best routes, and the travel times reach a more or less stable value. The two mean travel times are not exactly equal. This is because some day-to-day changes still occur, and because the drivers do not change their route when the difference in travel times is small.

The TTS in the network is 761.1 veh·h on the first day, and 546.7 veh·h on the last day. This shows that the drivers learn to select a route that leads to a lower cost.

The second simulation is done with variable speed limits used as an incident detection or warning system (as they are currently often used in, e.g., The Netherlands, in order to slow down traffic upstream of a congestion). This works as follows. When the speed in a segment drops below 40 km/h the speed limit in this segment is set on 50 km/h and the speed limit in the upstream segment on 70 km/h. When the speed increases above 50 km/h, the speed limits are no longer active. On the VMS instantaneous travel times are shown, mainly to inform the drivers.

In Figure 6 it can be seen that with this method the constant values of the travel times are reached within 12 days, and the maximum mean travel time stays lower. But the turning rates, shown in Figure 5 keep varying more than without control. This is due to the fact that more drivers switch route based on the given information.

The TTS on the first day is 512.3 veh·h, and on the last day it is 542.1 veh·h. This shows that many drivers react on the provided information the first day, but that they do not

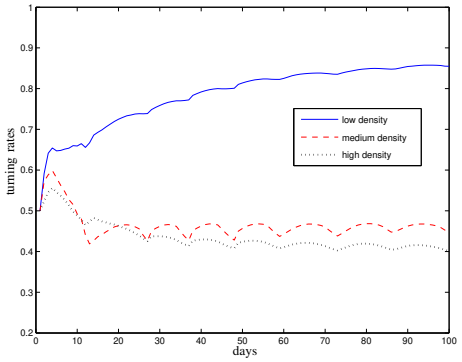

Fig. 5. Turning rates with variable speed limits as incident detection tool

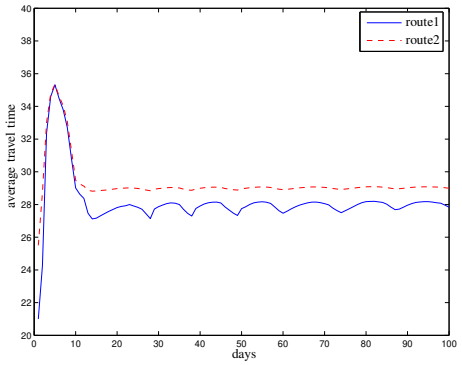

Fig. 6. Travel times with variable speed limits as incident detection tool

experience the same travel time as presented on the VMS. As a result, their belief in the information decreases and they start to neglect the information, which leads to nearly the same traffic assignment as without control.

The last simulation shows the effect of the MPC method described in this paper. Figures 7 and 8 show the results.

The TTS on the last day is 533.5 veh·h, which is only an improvement of 3% compared to no control, and of 2% to the method with variable speed limits as incident detection tool. A contribution of the developed MPC based method can be seen in the first 10 to 15 days. The high peak in average travel times is prevented, showing that the drivers learn faster what the best route is. It can also be seen that during the next days a more stable situation occurs, there are less fluctuations in travel times, making the routes more reliable. A side effect is that more drivers use the first route, which is shorter in distance and thus leads to less vehicle kilometers.

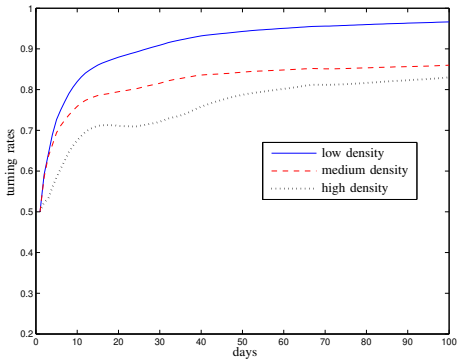

Fig. 7. Turning rates using integrated MPC

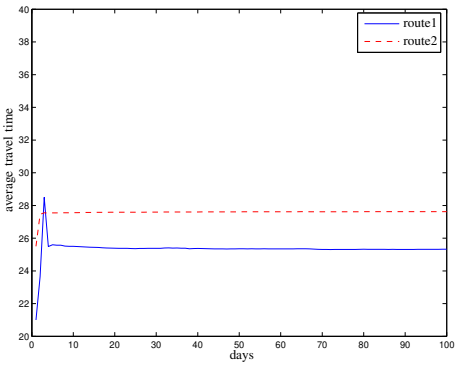

Fig. 8. Average travel times using integrated MPC

VII. Conclusion

Traffic control on freeways is often done with ramp metering or speed limits. Information is only used to inform the drivers about the current state of the network. In this paper we have considered the use of information to improve the performance of the network. We have developed an integrated control method using variable message signs with travel time information, and variable speed limits or other 'hard' control measures. The integrated control method uses a prediction model to predict the traffic over a specified period, and optimizes the control signals for this period. We have presented a probability-based route choice model which described the day-to-day as well as the within-day route choice. We have also described the reaction on the control methods.

In a simple case study we have illustrated the performance of the route choice model, and compared the integrated MPC control method with currently used control methods. This resulted in an improvement of 3%, with as main results more stable travel times and avoidance of peaks caused by drivers that are unfamiliar with the network.

Future research will focus on including urban roads into the system. Validation and calibration of the model, and robustness tests of the controller will be done. After these a real-life case study can be performed. Furthermore, we will investigate the scalability of the method for larger networks, and the possibilities to include other control measures.

Acknowledgment

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