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Control of traffic with anticipative ramp metering

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Abstract. When there are different routes from origin to destination in a network, the traffic divides itself over these routes. The resulting assignment is often determined by the travel times on the different routes. When control measures are implemented the travel times for some routes change, which can lead to a change in the assignment. This change in assignment can effect the performance of the whole network, but is often not automatically included in the traffic control frameworks.

In this paper we develop a control method that takes these re-routing effects into account. A model-based predictive control approach is used to determine optimal settings for traffic control measures. This control method stays optimal even when the route choice of the drivers changes. The method predicts the evolution of the traffic flows and the resulting traffic assignment, and uses this prediction to obtain the optimal control settings. To predict the traffic assignment a model is developed that, due to a low computational complexity, can be used in the controller.

As an example we apply the control method on ramp metering control for a freeway network. With a case study on a small network we show the effects of the method for ramp metering, and compare it with ALINEA, an existing ramp metering control method.

1 INTRODUCTION

Traffic jams form an increasing problem on the roads because they result in unpredictable delays and costs. A directly applicable solution is to decrease the traffic jams by improving the existing traffic control systems. On freeways these traffic control measures e.g. are variable speed limits, tidal flows, lane closures, variable message boards, and ramp metering. They often allow higher flows and throughputs. Many control methods exist to determine the settings of this measures (*7, 9, 12, 13*). To improve the functioning of the current measures a control structure must be developed that takes the reaction of the traffic on these measures into account. This reaction can consist of adaptation of the speed, lane changing, queuing, or selection of another route.

In this paper we look at the change in route choice due to control measures. It is clear that route choice is partly based on travel times (*6, 18*). While control measures influence the travel times, they also influence the route choice. This can result in a total different amount of traffic on a route, which requires a different traffic control strategy. The current control strategy can be improved by taking this change of route choice into account on beforehand when determining the measure settings.

We develop a control strategy that can handle these re-routing effects. The current traffic assignment and state are determined, and then a model is used to predict the behavior of the traffic. This behavior leads to certain travel times, and then a new traffic assignment is predicted based on these travel times. This new assignment is used in the optimization process to select the best settings for the coordinated traffic control measures.

Most of the existing traffic control measures have some disadvantages. A disadvantage of ramp metering e.g. is that it causes queues on the on-ramps. These queues can become so long that they block intersections near the freeway. To prevent this, the control strategy must be able to deal with queue length constraints. Therefore, we propose to use a model predictive control (MPC) approach (*4, 10*). This method has already been applied for different freeway networks (*3, 8, 1*), and can handle hard constraints.

MPC requires a model that predicts the evolution of the traffic flows on the network. For the driving behavior of the traffic we have selected a macroscopic traffic model, the METANET model, developed by Messmer and Papageorgiou (*11, 20*). To be able to apply anticipating control it is necessary to describe also the re-routing of the traffic flows. Currently existing methods take quite some computation time, and slow down the predictions too much. In this paper we develop a coordinated control strategy which does not take too much time, but still gives sufficiently good results.

This paper is organized as follows. Section 2 describes the traffic model that is used to predict the traffic behavior. The method used to predict the route choice is described in Section 3. In Section 4 the model predictive control strategy is explained. Note that this control strategy is used for ramp metering in this paper, but that the presented technique can also be applied to other integrated measures like variable speed limits of dynamic special lanes. At last we describe a simple network used for a case study in Section 5, where we show the improvement compared to the results reached with the local ALINEA control method.

2 THE METANET MODEL FOR FREEWAY TRAFFIC

To describe the traffic on the freeway we use the METANET model developed by Papageorgiou and Messmer (*11, 20*). In METANET the freeway network is represented as a graph with nodes and links, where the links correspond to freeway stretches with uniform characteristics; the nodes are placed at on-ramps and off-ramps, where two or more freeways connect, or where the characteristics change. Links are divided into one of more segments with a length of about 500 m.

The evolution of the traffic system is characterized by the average density $\rho_{m,i}(k_\mathrm{f})$, flow $q_{m,i}(k_\mathrm{f})$, and speed $v_{m,i}(k_\mathrm{f})$ for each segment i of each link m at time $t = k_\mathrm{f} T_\mathrm{f}$:

$$\begin{aligned}
\rho_{m,i}(k_\mathrm{f}+1) &= \rho_{m,i}(k_\mathrm{f}) + \frac{T_\mathrm{f}}{L_m n_m}\left[q_{m,i-1}(k_\mathrm{f}) - q_{m,i}(k_\mathrm{f})\right] \\
q_{m,i}(k_\mathrm{f}) &= \rho_{m,i}(k_\mathrm{f}) v_{m,i}(k_\mathrm{f}) n_m \\
v_{m,i}(k_\mathrm{f}+1) &= v_{m,i}(k_\mathrm{f}) + \frac{T_\mathrm{f}}{\tau}(V(\rho_{m,i}(k_\mathrm{f})) - v_{m,i}(k_\mathrm{f})) + \\
&\quad \frac{T_\mathrm{f}}{L_m} v_{m,i}(k_\mathrm{f}) \left[v_{m,i-1}(k_\mathrm{f}) - v_{m,i}(k_\mathrm{f})\right] - \\
&\quad \frac{\nu T_\mathrm{f}[\rho_{m,i+1}(k_\mathrm{f}) - \rho_{m,i}(k_\mathrm{f})]}{\tau L_m [\rho_{m,i}(k_\mathrm{f}) + \kappa]}
\end{aligned} \tag{1}$$

where T_f, L_m, $V(\rho_{m,i}(k_\mathrm{f}))$ and n_m respectively are the time step for freeway simulation, the length of the segments of freeway link m, the desired speed of the drivers on segment i of freeway link m, and the number of lanes of freeway link m, while τ, ν and κ are parameters. The desired speed $V(\rho_{m,i}(k_\mathrm{f}))$ is computed as follows:

$$V(\rho_{m,i}(k_\mathrm{f})) = v_\mathrm{free} \exp\left[-\frac{1}{a_m}\left(\frac{\rho_{m,i}(k_\mathrm{f})}{\rho_\mathrm{crit}}\right)^{a_m}\right] \tag{2}$$

where v_free is the free flow speed and ρ_crit is the critical density, i.e. the density where congestion starts to appear.

Remark 1: Note that here the index k_f (with subscript f) is used to denote the freeway simulation step counter. This to make a clear difference with the controller sample step, for which we will introduce the index k_c later on in Section 4. $\diamond$

At nodes with more upstream links and one downstream link the incoming flows are summed up, and the influence on the arriving traffic is described by adding a merging term to the speed equation:

$$v_{m,0} = \frac{\sum_{g \in O_m} v_{g,N_g}(k_\mathrm{f}) q_{g,N_g}(k_\mathrm{f})}{\sum_{g \in O_m} q_{g,N_g}(k_\mathrm{f})} \tag{3}$$

where O_m is the set of freeways entering the node connected to downstream freeway m, and where N_g is the last segment of freeway g.

At nodes with more than one leaving link the arriving flow is divided over the leaving links according to:

$$q_{m,0}(k_\mathrm{f}) = \beta_{n,m}(k_\mathrm{f}) q_{\mathrm{tot},n}(k_\mathrm{f})$$

where n gives the node index, m the index of the downstream freeway links, and $q_{\mathrm{tot},n}$ the total flow at the node. The value of the splitting rates $\beta_{n,m}(k_\mathrm{f})$ will be computed by the assignment algorithm described in the next section.

3 METHOD TO COMPUTE THE DYNAMIC TRAFFIC ASSIGNMENT

Traffic flows divide themselves over the network when there exist more routes between origins and destinations. It appears that every driver assigns a cost $C_r(k_\mathrm{f})$ to every possible route r, and selects the route with the lowest cost. As a result a user equilibrium will be reached, where the costs of alternative routes are equally high (*24*).

The cost function can contain many different terms, such as the length of the road, the number of intersections, the environment or the travel time. In this paper we only use the travel time to describe the cost of a route, as suggested in (*6, 18*). The travel time is computed as follows:

$$C_r(k_\mathrm{f}) = \sum_{(m,i)\in M_r} \frac{L_m}{v_{m,i}(k_\mathrm{f})} \ ,$$

where M_r is the set of pairs of indexes (m, i) of all links and segments belonging to route r.

The equilibrium assignment is now reached when the travel times on alternative routes are equal. But because the traffic demands and situations change over time the costs on alternative routes will never reach this real equilibrium. So to give a good description of the evolution of the traffic assignment a dynamic method is required. Our dynamic method consists of two parts. First the 'current equilibrium assignment' for the current state and demand is determined. Next the evolution from the current assignment toward this 'current equilibrium assignment' is described.

The 'current equilibrium assignment' is the assignment that gives equal travel times from origin to destination for vehicles that enter the network at the current time. This means that existing congestion and speed are taken into account while computing the travel times. But the state of the network is not exactly known by the drivers. Therefore we assume that the drivers have been gathering information about the traffic for some time span τ_info. They use this information to determine their route choice, which will lead to a 'perceived current equilibrium traffic assignment' during the time they travel in the network. The larger τ_info, the slower the response of the route choice behavior of the drivers to varying traffic demands and metering rates will be.

To compute an equilibrium assignment there exist several methods, some of them described in (*18, 21, 23, 25*). In this paper we use the 'Method of the Successive Averages' (MSA) (*17*). MSA is an iterative method that computes the cost of different routes according to the flow $q_{r,j}$ on each route r in iteration j. The travel times, and thus the costs for each route, that result from these flows are determined using a prediction of the traffic flows over the period $[k_\mathrm{f}T_\mathrm{f}, (k_\mathrm{f} + N_\mathrm{MSA})T_\mathrm{f})$ with the METANET model, where N_MSA is the prediction horizon for the MSA algorithm. Then all traffic is assigned to the route with the lowest cost, resulting in the all-or-nothing assignment flows $q^\mathrm{MSA}_{r,j}(k_\mathrm{f})$. These flows are used to compute the flows for the next iteration:

$$q^\mathrm{MSA}_{r,j+1}(k_\mathrm{f}) = \left(1 - \frac{1}{j}\right) q^\mathrm{MSA}_{r,j}(k_\mathrm{f}) + \left(\frac{1}{j}\right) q^\mathrm{AON}_{r,j}(k_\mathrm{f})$$

where $q^\mathrm{MSA}_{r,j}$ is the flow towards route r during iteration j of the MSA algorithm, and $q^\mathrm{AON}_{r,j}$ the flow towards route r determined by the all or noting assignment after iteration 'j. The stopping criterion is based on a maximum value for the difference between two successive iteration flows: when the difference is below this specified value the algorithm terminates. To prevent long computation times the algorithm will also exit when a maximum number of iterations is reached. The resulting flows are used to determine the equilibrium split rates:

$$\beta^{\mathrm{MSA}^*}_{n_r,m_r}(k_\mathrm{f}) = \frac{q^*_{r,j_\mathrm{final}}}{D_{o_r,d_r}(k_\mathrm{f})}$$

with q^*_{r,j_final} the equilibrium flow determined with the MSA algorithm, $\beta^{\mathrm{MSA}^*}_{n_r,m_r}$ the spit rates on node n_r belonging to route r toward link m_r which also belongs to route r, and $D_{o_r,d_r}(k_\mathrm{f})$ the total demand from origin o_r to destination d_r, of route r passing through node n_r.

Next we determine the dynamic traffic assignment to cope with changes in the traffic. Several methods exist to compute dynamic traffic assignments based on a cost function (see (*2, 5, 20, 22*)). A disadvantage of these models is often that they require much computation time. For the use in real-time model-based controllers the assignment must be computed every controller time step and so these models cannot be used.

We assume that the flows ideally will divide themselves according to the 'perceived current equilibrium assignment' described before. But because not all the drivers respond to the changes immediately we assume that the current traffic assignment will change toward this equilibrium assignment in an exponential way. This results in an adaptation of the splitting rates according to:

$$\beta_{n_r,m_r}(k_\mathrm{f}+1) = \beta_{n_r,m_r}(k_\mathrm{f}) + (\beta^{\mathrm{MSA}^*}_{n_r,m_r}(k_\mathrm{f}) - \beta_{n_r,m_r}(k_\mathrm{f}))(1 - e^{-\frac{T_\mathrm{f}}{\tau_\mathrm{reac}}}) \ . \tag{4}$$

Here the parameter τ_reac influences how fast the current assignment converges toward the presumed equilibrium assignment. This swiftness depends on the time that is needed for the effects of a congestion to reach the drivers that still have to make their route choice.

The equilibrium, and thus the resulting assignment computed with (4), will differ from the real situation because it is based on an estimation of the current state of the network. We keep this difference small by updating the presumed equilibrium assignment and computing new splitting rates every T_update seconds.

4 ANTICIPATIVE RAMP METERING USING MODEL PREDICTIVE CONTROL

The control method we use is based on MPC. This method contains the following elements: a performance criterion, a prediction model, constraints and the receding horizon principle. The developed method can be used for many traffic control measures (*1, 3, 8*), but for the case study we only apply it for ramp metering.

Traffic entering the freeway from an on-ramp can cause congestion because the volume is too large or because it arrives in platoons. Ramp metering is a control measure that diverts the traffic over time and limits the entering flow. The metering rate $p(k_\mathrm{f})$ gives the fraction of the maximum capacity flow of the on-ramp that is allowed to depart toward the freeway. The flow entering the freeway is then given by

$$q_{\mathrm{ramp},o}(k_\mathrm{f}) = \min\left[D_{\mathrm{ramp},o} + \frac{w_o(k_\mathrm{f})}{T_\mathrm{f}}, Q_{\mathrm{cap},o}\min(p_o(k_\mathrm{f}), \frac{\rho_{\mathrm{jam},m_o} - \rho_{m_o,1}(k_\mathrm{f})}{\rho_{\mathrm{jam},m_o} - \rho_{\mathrm{crit},m_o}})\right]$$

with w_o the number of vehicles waiting at the on-ramp origin o, $Q_{\mathrm{cap},o}$ the maximum capacity flow of the on-ramp, m_o the freeway link connected to the on-ramp, ρ_{jam,m_o} the maximal density on freeway link m_o, and ρ_{crit,m_o} the density where congestion starts on segment m_o.

Remark 2: The settings of the control measures are computed every controller time step. For ease of notation we first define the set of simulation steps k_f that correspond to a given interval $[k_\mathrm{c}^a, k_\mathrm{c}^b]$ of controller time steps as follows:

$$\mathcal{K}_\mathrm{f}(k_\mathrm{c}^a, k_\mathrm{c}^b) = \left[k_\mathrm{c}^a\frac{T_\mathrm{c}}{T_\mathrm{f}}, k_\mathrm{c}^a\frac{T_\mathrm{c}+1}{T_\mathrm{f}}, ..., k_\mathrm{c}^b\frac{T_\mathrm{c}}{T_\mathrm{f}} - 1\right]$$

where k_c is the control step and T_c is the control sample time. $\diamond$

Different methods exist to determine the metering rate (see (*14*) or (*16*) for an overview). We propose an on-line model-based predictive control design strategy called Model Predictive Control (MPC). This control strategy uses an indicator to determine the performance of the network. As 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). The TTS can be computed as:

$$\mathrm{TTS}(k_\mathrm{c}) = T_\mathrm{f} \sum_{k_\mathrm{f} \in \mathcal{K}_\mathrm{f}} \left(\sum_{(m,i) \in M} L_m n_m \rho_{m,i}(k_\mathrm{f}) + \sum_{o \in O} w_o(k_\mathrm{f}) \right)$$

where M is the set of pairs of indexes (m, i) of all links in the network, and O the set of origins.

The MPC strategy can handle hard constraints. This makes it possible to prevent blocking of urban intersections or too long waiting times by setting constraints on the queue length or the metering rates:

$$w_o(k_\mathrm{f}) \leq w_o^{\max}$$

$$p^{\min} \leq p(k_\mathrm{f}) \leq p^{\max} \ .$$

The MPC control strategy works as follows (*4, 10*). At a given time $t = k_\mathrm{c} T_\mathrm{c} = k_\mathrm{f} T_\mathrm{f}$ the MPC controller uses the prediction model METANET and numerical optimization to determine the optimal ramp metering sequence $p^*(k_\mathrm{c}), \ldots, p^*(k_\mathrm{c} + N_\mathrm{p} - 1)$ that minimizes the given performance indicator $\mathrm{TTS}(k_\mathrm{c})$ 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 $p^*(k_\mathrm{c})$ is applied to the system during the period $[k_\mathrm{c} T_\mathrm{c}, (k_\mathrm{c} + 1) T_\mathrm{c})$. Before the sample $p^*(k_\mathrm{c})$ can be used, it must be sampled on the freeway simulation time step:

$$p(k_\mathrm{f}) = p^*(k_\mathrm{c}) \text{ for } k_\mathrm{f} \in \mathcal{K}_\mathrm{f}(k_\mathrm{c}, k_\mathrm{c} + 1) \ . \tag{5}$$

When the first sample is applied the horizon is shifted, new measurements are made, and the process is repeated all over again.

The MPC controller uses a prediction of the traffic states during the period $[k_\mathrm{c} T_\mathrm{c}, (k_\mathrm{c} + N_\mathrm{p}) T_\mathrm{c})$. To determine this prediction a prediction of the splitting rates during the same period is required. To obtain this we use the algorithm described in Section 3.

Because the controller should see the influence of the settings on the route choice, the equilibrium should be updated several times during the prediction horizon. The time step for updating the assignment, which for the controller is denoted by T_anticip, must be selected according to:

$$N T_\mathrm{anticip} \leq N_\mathrm{p} T_\mathrm{c} \tag{6}$$

with N an integer larger than 1. The exact value of T_anticip depends on the re-routing dynamics in the network which depend on the topology of the network (*19*). The re-routing dynamics are typically much slower than the dynamics of the traffic system near the on-ramps.

A trade-off can be made between the accuracy of the traffic assignment and the computational complexity of the anticipative traffic assignment by tuning the time T_anticip between two updates.

5 RESULTS OF A CASE STUDY

A simple network will be used to illustrate the effects of the MPC-based anticipative ramp metering control. The layout of the network is shown in Figure 1, where the arrow gives the direction of the traffic flows. The network consists of a freeway with four lanes that bifurcates into two branches of two lanes each. Downstream both branches join in a four-lane freeway. Both four-lane freeway links are 3 km long. The lower two-lane branch is the primary branch. The primary branch is 6 km long and an on-ramp is present in the middle of the branch. The secondary branch is longer than the primary branch and is 8 km long. Route 1 follows the primary branch, and route 2 the secondary. The traffic originating from the mainstream origin distributes over the two branches using the route choice mechanism described in Section 3.

Two simulations have been done. One with the existing ramp metering strategy ALINEA, and one with the MPC-based method. ALINEA is developed by Papageorgiou *et al*, (*15*). It determines the metering rate by comparing the occupancy of the freeway segment downstream the on-ramp with a desired occupancy, that we have chosen equal to the critical occupancy as recommended in (*15*). The metering rate is determined as follows:

$$p(k_\mathrm{c}) = p(k_\mathrm{c} - 1) + K(o_\mathrm{crit} - o_{m,1}(k_\mathrm{c})) \tag{7}$$

where $o_{m,1}$ is the occupancy on the first segment of freeway m downstream of the on-ramp, o_crit the critical occupancy of this segment, and K the gain.

The MPC method is developed for integrated/coordinated control, but to be able to compare it with ALINEA only one ramp metering installation is simulated. In this case study the following parameter settings are used: τ_info = 30 min, τ_reac = 45 min, T_update = 15 min, T_anticip = 5 min, T_f = 10 s, T_c = 1 min, N_p = 15 min, p^max = 1, p^min = 0.1. A period of four hours is simulated.

We simulate a traffic scenario with a constant traffic demand at the mainstream origin equal to 4500 veh/h. The traffic demand on the on-ramp is 100 veh/h at the start of the simulation, increases to 800 veh/h after one hour and decreases again to 100 veh/h after two hours, see Figure 2.

The results of the simulation with ALINEA ramp metering are shown in Figure 3.

At 7 a.m. the peak in the on-ramp demands starts. Figure 3(a) shows the increase in density on the segment downstream of the on-ramp at that moment. As a reaction on this high density the metering signal becomes active and goes to zero, as can be seen in Figure 3(b). This low metering rate causes a drop in the density below the original density. This drop has two effects: more drivers choose the first route so the split rates change (Figure 3(c)), and the metering rate becomes higher, so more traffic can enter the freeway, as shown in Figure 3(d). Then the density increases again, and converges to the critical density after 7.45 a.m. The critical density is the set-point of the metering rate, and so the controller will try to keep the density on this value, in which it succeeds for the rest of the simulation. In Figure 3(e) the travel times on the two routes are shown. Since at 7.30 a.m. the travel time on route 1 is longer than on route 2, the split rates (Figure 3(c)) change so more traffic starts taking route 2. This leads to a slowly decreasing amount of traffic on route 1, resulting in a lower density. The metering signal reacts on the lower density and starts to increase after 7.45 a.m. resulting in a slowly increasing flow on the on-ramp, as can be seen in Figure 3(d). The last sub-figure 3(f) shows the queue on the on-ramp. At 7.10 a.m. the ramp metering signal becomes active, and the queue starts to grow. After 8.00 a.m. the peak of the on-ramp demand ends, and the queue starts to empty.

The total time spent in the network was 3618.9 veh·h for the ALINEA method.

The results obtained with the anticipative MPC strategy are shown in Figure 4. As the peak in the on-ramp demand starts, the density on the segment downstream of the on-ramp increases (Figure 4(a)).

When this density becomes to high, the metering rate decreases, as shown in Figure 4(b). But it keeps the density above the critical density, on 40 veh/lane/km. This means that the travel time on the first route, which is shown in Figure 4(e), stays high, resulting in more drivers selecting route 2 (see Figure 4(c)). On the on-ramp a queue starts to grow, until 8 a.m. At this moment the peak in the on-ramp demand ends, and now the queue starts to empty. Much traffic enters the freeway from the on-ramp, as can be seen in Figure 4(d), resulting in a longer travel time on route 1, and thus more traffic turning toward route 2. But then the density becomes lower and the travel times decrease, leading to more drivers selecting route 1. After 9 a.m. The flow from the origin becomes more stable, the queue empties, resulting in longer travel times, and more traffic selecting route 2.

The total time spent in the network was 3300.5 veh·h for the MPC-based control method, which is an improvement of 9% compared to ALINEA.

6 CONCLUSIONS

In networks where drivers can choose different routes from their origin to destination, they assign a cost to each route, and choose the route with the lowest cost. An important factor in this cost is the travel time. Since control measures can influence the travel times, they can influence the cost of each route. This change in the costs can make the driver select another route, resulting in another traffic assignment in the network.

In this paper we have developed a control strategy based on model predictive control (MPC) that takes the re-routing of traffic into account. MPC uses the prediction of the network to optimize a performance index. A model is used to predict the behavior of the traffic in the network. As model for the freeway traffic we have selected the METANET model. To describe the evolution of the traffic assignment we have developed an algorithm based on the Method of Successive Averages (MSA). The dynamic algorithm describes exponential convergence from the current traffic assignment toward the equilibrium assignment. As control measure we have selected ramp metering, but the method can be applied to other control measures as well.

In a case study we have simulated a small network with two possible routes. The developed MPC structure is compared with the ALINEA method with ramp metering as control measure. The performance of the MPC method was 9% better than the performance with ALINEA.

Topics for further research are: investigation of the trade-off between accuracy and computational complexity; simulation of larger networks with more control measures; inclusion of other traffic assignment methods; including the influence of variable message boards on the route choice.

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LIST OF FIGURES

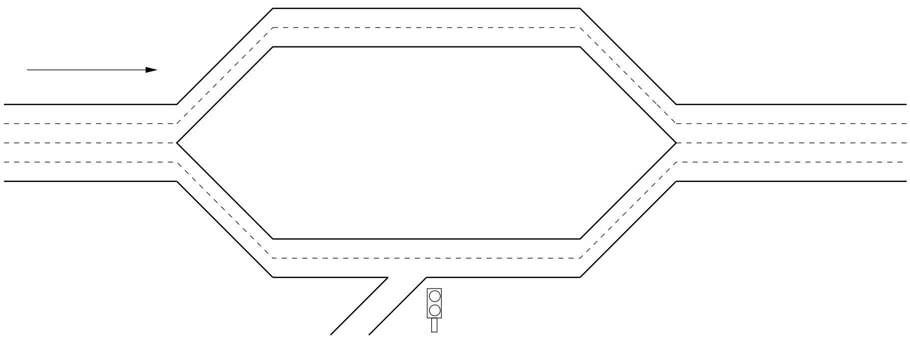


FIGURE 1 Schematic representation of the freeway network of the case study.

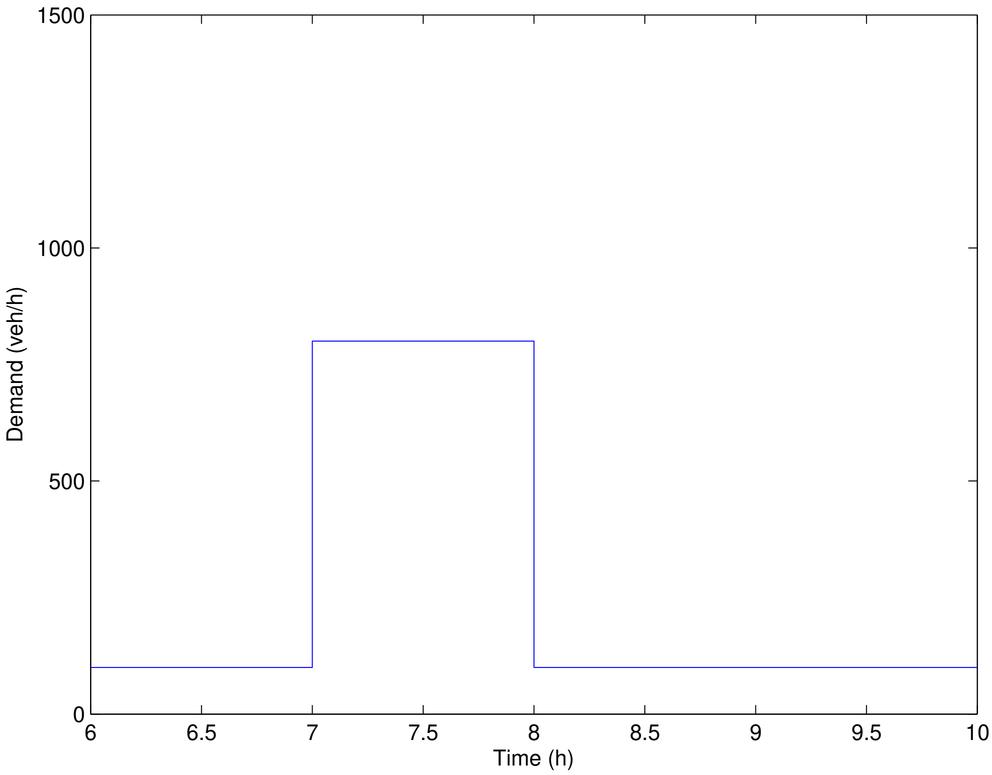
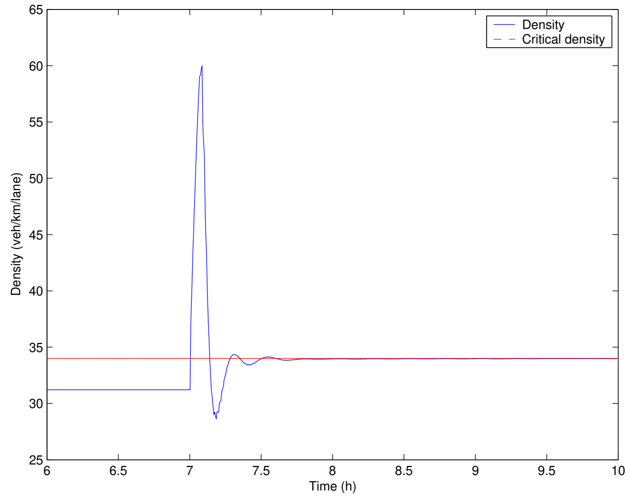
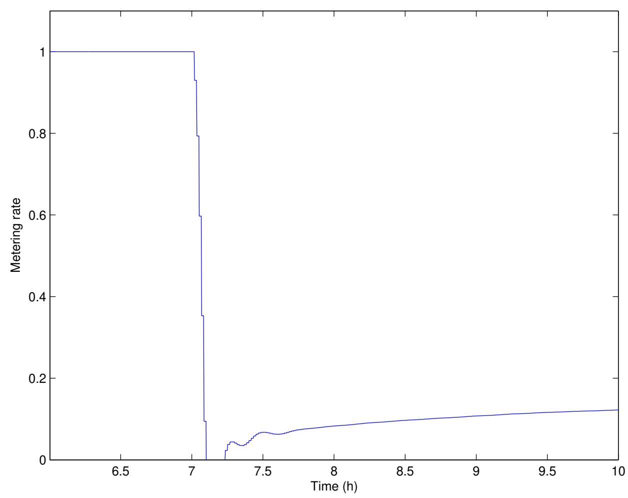


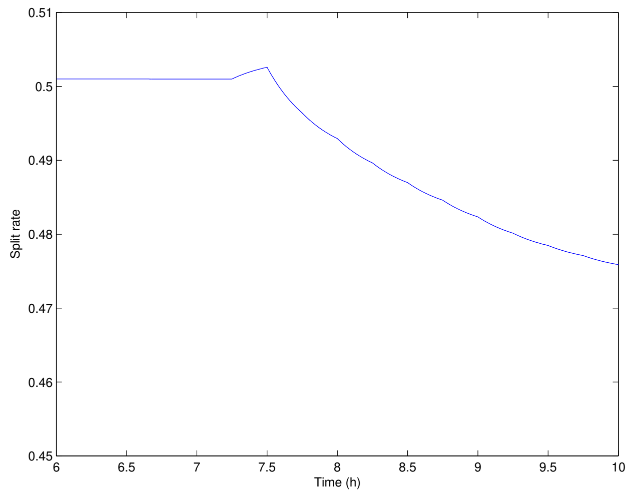
FIGURE 2 Traffic demand on the on-ramp



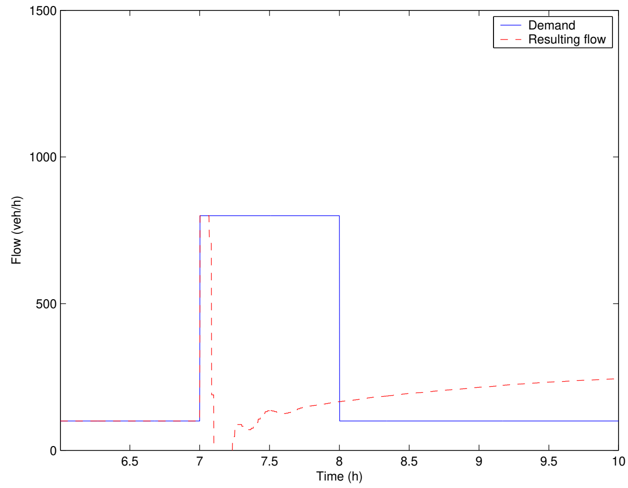
(a) Density on the segment downstream the on-ramp



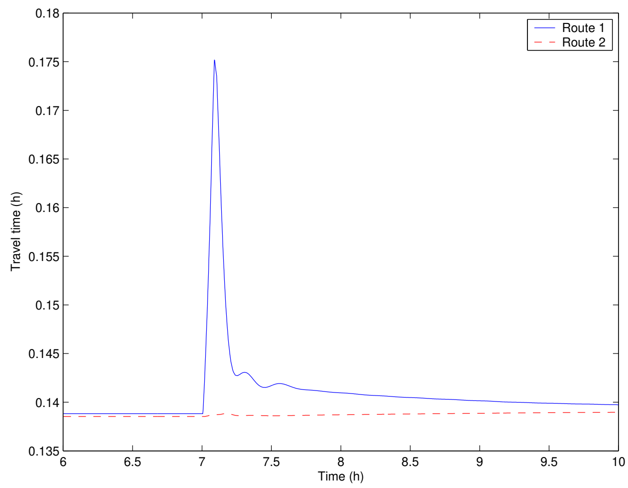
(b) Metering rates



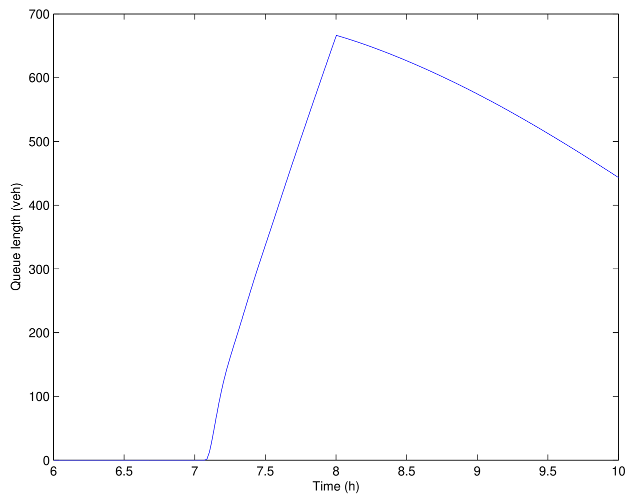
(c) Split rate toward route 1



(d) Flow on the on-ramp

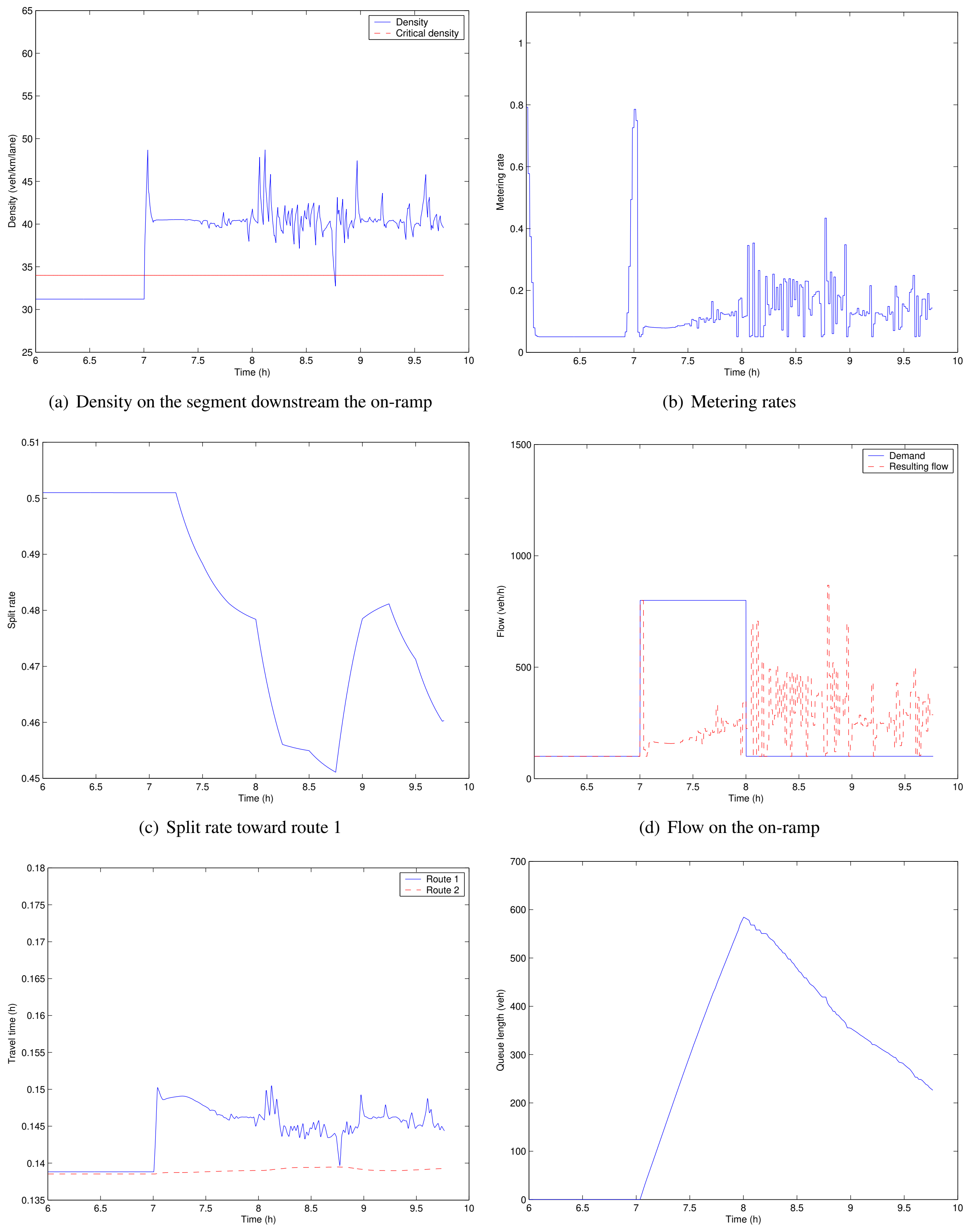


(e) Travel times on the two routes



(f) Queue length on the on-ramp

FIGURE 3 Simulation results with ALINEA ramp metering



(a) Density on the segment downstream the on-ramp

(b) Metering rates

(c) Split rate toward route 1

(d) Flow on the on-ramp

(e) Travel times on the two routes

(f) Queue length on the on-ramp

FIGURE 4 Simulation results with MPC-based ramp metering