Coordinated ramp metering for freeway networks – A model-predictive hierarchical control approach

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Abstract

A nonlinear model-predictive hierarchical control approach is presented for coordinated ramp metering of freeway networks. The utilized hierarchical structure consists of three layers: the estimation/prediction layer, the optimization layer and the direct control layer. The previously designed optimal control tool AMOC (Advanced Motorway Optimal Control) is incorporated in the second layer while the local feedback control strategy ALINEA is used in the third layer. Simulation results are presented for the Amsterdam ring-road. The proposed approach outperforms uncoordinated local ramp metering and its efficiency approaches the one obtained by an optimal open-loop solution. It is demonstrated that metering of all on-ramps, including freeway-to-freeway intersections, with sufficient ramp storage space leads to the optimal utilization of the available infrastructure.

Keywords: Coordinated ramp metering; Hierarchical control; Model-predictive control; AMOC; ALINEA
1. Introduction

Ramp metering aims at improving the freeway traffic conditions by appropriately regulating the inflow from the on-ramps to the freeway mainstream. Ramp metering strategies can be classified as fixed-time or traffic-responsive (see Papageorgiou and Kotsialos, 2002, for an overview). Fixed-time strategies are derived off-line for particular times of the day, based on historical demands (see, e.g., Wattleworth, 1965). Due to the absence of real-time measurements, they may lead either to overload of the mainstream flow (congestion) or to underutilization of the freeway.

Traffic-responsive ramp metering strategies are based on real-time measurements from sensors installed in the freeway network and the on-ramps and can be further classified as local or coordinated. Local ramp metering strategies make use of measurements from the vicinity of a single ramp and include feed-forward control approaches, such as the demand-capacity strategy and its variations (Masher et al., 1975), feedback control approaches, such as the ALINEA strategy and its variations (Papageorgiou et al., 1991, 1998; Smaragdis and Papageorgiou, 2003; Smaragdis et al., 2004), as well as neural network (e.g., Zhang and Ritchie, 1997) or fuzzy-logic based (e.g., Vukanovic and Ernhofer, 2006) approaches. On the other hand, coordinated ramp metering strategies make use of measurements from an entire region of the network to control all metered ramps included therein. Coordinated ramp metering approaches include multivariable control strategies (e.g., Papageorgiou et al., 1990b; Diakaki and Papageorgiou, 1994), optimal control strategies (e.g., Papageorgiou and Mayr 1982; Zhang et al., 1996; Chen et al., 1997; Zhang and Recker, 1999; Bellemans et al., 2002; Hegyi et al., 2003; Zhang and Levinson, 2004; Gomes and Horowitz, 2006), and further heuristic algorithms.
(Jackobson et al., 1988; Hourdakis and Michalopoulos, 2002; see Hadi, 2005, for an overview).

Local ramp metering applied independently to multiple ramps of a freeway network would be highly efficient in case of unconstrained ramp queues for vehicle storage. However, ramp queues must be restricted to avoid interference with adjacent street traffic, in which case mainstream congestion may be reduced but cannot be avoided by merely local control. Thus, limited ramp storage space and the requirement of equity (for drivers using different on-ramps) are the main reasons for coordinated ramp metering.

Another major issue to be adequately addressed when designing traffic-responsive ramp metering strategies, is the manifest uncertainty of the mainstream flow capacity. Recent works (Elefteriadou et al., 1995; Lorenz and Elefteriadou, 2001; Cassidy and Rudjanakanoknad, 2005) have demonstrated that traffic breakdown in merge areas may occur at different flow values on different days, even under similar environmental conditions. Naturally, highway capacity differences become even more pronounced in case of adverse environmental conditions (Keen et al., 1986). In contrast, the critical occupancy (at which capacity flow occurs) was found to be fairly stable (Cassidy and Rudjanakanoknad, 2005) even under adverse environmental conditions (Keen et al., 1986; Papageorgiou et al., 2006). In view of the uncertainty of real highway capacity, any ramp metering strategy attempting to achieve a pre-specified capacity flow value, will either lead to overload and congestion (on days where the real capacity happens to be lower than its pre-specified value) or to underutilization of the infrastructure (on days where the real capacity happens to be higher than its pre-specified value). Note that
most known coordinated ramp metering strategies belong to this class; in particular, model-based optimal control strategies (even those employing a model-predictive application mode) belong to this class with a pre-specified capacity value included in their model parameters (unless their capacity-related model parameters are estimated sufficiently accurately and rapidly in real time). The only known ramp metering strategies that target the (more stable) critical occupancy (rather than capacity) is ALINEA, a local strategy, and its aforementioned multivariable-regulator extensions. The issue of highway capacity uncertainty is explicitly considered when designing a hierarchical ramp metering strategy in this paper.

Kotsialos et al. (2002b) presented AMOC, an open-loop optimal control tool for large-scale freeway networks including a powerful numerical optimization algorithm. AMOC is able to consider coordinated ramp metering, route guidance and, recently, variable speed limits as well as integrated control combining any of the mentioned control measures. Kotsialos and Papageorgiou (2001, 2004) presented in detail the results from AMOC’s application to the problem of coordinated ramp metering at the Amsterdam ring-road.

Due to various inherent uncertainties (including the capacity uncertainty), the open-loop optimal solution delivered by optimal control approaches becomes suboptimal when directly applied to the freeway traffic process. Therefore, in this paper, the AMOC optimal results are cast in a model-predictive frame; in addition, to improve control robustness even further and address the particular capacity uncertainty, sub-ordinate local regulators (ALINEA) are introduced with set-points derived appropriately from AMOC’s optimal results. This leads to a hierarchical control scheme similar to that
proposed by Papageorgiou (1984), albeit with a more sophisticated optimal control methodology. Preliminary results of this approach have been presented by Kotsialos et al. (2005).

The rest of this paper is organized as follows. In section 2 the freeway network traffic flow model used for both simulation and control design purposes is presented. Section 3 introduces the formulation of the AMOC optimal control problem for ramp metering. The hierarchical control structure is described in section 4 while the results of applying ALINEA, as a stand-alone strategy, as well as the proposed hierarchical control scheme are presented and compared in section 5. The main conclusions are summarized in section 6.

2. Traffic flow modeling

A validated second-order traffic flow model is used for the description of traffic flow on freeway networks and provides the modeling part of the optimal control problem formulation. In fact, the same model is used in this study for the traffic flow simulator (METANET) and for the control strategy (AMOC) albeit with different external disturbances (i.e., demands and turning rates) and model parameter values affecting capacity. Since traffic assignment aspects of the traffic process are not absolutely necessary when the only type of control measure applied is ramp metering, the traffic assignment modeling part will not be presented (see Messmer and Papageorgiou, 1990, for details).

The network is represented by a directed graph whereby the links of the graph represent freeway stretches. Each freeway stretch has uniform characteristics, i.e., no on-/off-ramps and no major changes in geometry. The nodes of the graph are placed at locations
where a major change in road geometry occurs, as well as at junctions, on-ramps, and off-ramps.

The time and space arguments are discretized. The discrete time step is denoted by $T$ (typically $T = 10\text{s}$). A freeway link $m$ is divided into $N_m$ segments of equal length $L_m$ (typically $L_m = 500\text{m}$), such that the numerical stability condition $L_m \geq T \cdot v_{f,m}$ holds, where $v_{f,m}$ is the free speed of link $m$. This condition ensures that no vehicle traveling with free speed will pass a segment during one simulation time step. Each segment $i$ of link $m$ at discrete time $t = kT$, $k = 0, \ldots, K$, where $K$ is the time horizon, is macroscopically characterized via the following variables: the traffic density $\rho_{m,i}(k)$ (veh/km/lane) is the number of vehicles in segment $i$ of link $m$ at time $t = kT$ divided by $L_m$ and by the number of lanes $\Lambda_m$; the mean speed $v_{m,i}(k)$ (km/h) is the mean speed of the vehicles included in segment $i$ of link $m$ at time $t = kT$; and the traffic volume or flow $q_{m,i}(k)$ (veh/h) is the number of vehicles leaving segment $i$ of link $m$ during the time period $[kT, (k+1)T)$, divided by $T$. For each segment $i$ of link $m$ at each time step $k$, the following equations are applied:

\begin{align}
\rho_{m,i}(k+1) &= \rho_{m,i}(k) + \frac{T}{L_m \Lambda_m} \left[ q_{m,i-1}(k) - q_{m,i}(k) \right] \\
q_{m,i}(k) &= \rho_{m,i}(k) v_{m,i}(k) \Lambda_m \\
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} \left[ v_{m,i-1}(k) - v_{m,i}(k) \right] v_{m,i}(k) \\
&\quad - \frac{vT}{\tau L_m} \frac{\rho_{m,i+1}(k) - \rho_{m,i}(k)}{\rho_{m,i}(k) + \kappa}
\end{align}

(1)
\[ V[\rho_{m,i}(k)] = v_{f,m} \exp \left[ \frac{1}{\alpha_m} \left( \frac{\rho_{m,i}(k)}{\rho_{c,r,m}} \right)^{\alpha_m} \right] \]  \hspace{1cm} (4)

where \( \rho_{c,r,m} \) denotes the critical density per lane of link \( m \) (the density at which the traffic flow in the link reaches its capacity, \( q_{cap,m} \), under homogeneous and stationary conditions), and \( \alpha_m \) is a parameter of the fundamental diagram (4) of link \( m \) which expresses a nonlinear relationship between the mean speed and the traffic density. Furthermore, \( \tau \), a time constant, \( \nu \), an anticipation constant, and \( \kappa \), are further parameters which are equal for all the network links. Additionally, the mean speed resulting from (3) is limited from below by the minimum speed \( v_{min} \) in order to avoid unrealistically low flows during congestion. Two additional terms are added to Eq. (3) in order to consider the speed decrease caused by merging phenomena at a junction and by lane drops, respectively (see Papageorgiou et al., 1990a, for more details and model validation results).

For origin links, i.e., links that receive traffic demand \( d_o \) and forward it into the freeway network, a simple queue model is used (Figure 1). The outflow \( q_o \) of an origin link \( o \) depends on the traffic conditions of the corresponding mainstream segment \( (\mu,1) \) and the existence of ramp metering control measures. If ramp metering is applied, then the outflow \( q_o(k) \) that is allowed to leave origin \( o \) during period \( k \), is a portion \( r_o(k) \) of the outflow \( \hat{q}_o(k) \) that would leave in absence of ramp metering. Thus, \( r_o(k) \in [r_{min,o}, 1] \) is the metering rate for the origin link \( o \), i.e., a control variable, where \( r_{min,o} \) is a minimum admissible value; typically, \( r_{min,o} > 0 \) is chosen in order to avoid
ramp closure. If \( r_o(k) = 1 \), no ramp metering is applied, else \( r_o(k) < 1 \). The queuing model is described by the following conservation equation

\[
w_o(k+1) = w_o(k) + T \left[ d_o(k) - q_o(k) \right]
\]  

(5)

where \( w_o(k) \) is the queue length (veh) in origin \( o \) at time step \( k \), and \( d_o(k) \) is the demand (veh/h) at \( o \) at the same period. The outflow \( q_o \) is determined as follows:

\[
q_o(k) = r_o(k) \hat{q}_o(k)
\]  

(6)

with the non-metered flow

\[
\hat{q}_o(k) = \min \{ \hat{q}_{o,1}(k), \hat{q}_{o,2}(k) \}
\]  

(7)

and

\[
\hat{q}_{o,1}(k) = d_o(k) + w_o(k) / T
\]  

(8)

\[
\hat{q}_{o,2}(k) = Q_o \min \left\{ 1, \frac{\rho_{\text{max}} - \rho_{\mu,1}(k)}{\rho_{\text{max}} - \rho_{\mu,\mu}} \right\}
\]  

(9)

where \( Q_o \) is the on-ramp's capacity (veh/h), i.e., the on-ramp's maximum possible outflow under free-flow traffic conditions in the mainstream, and \( \rho_{\text{max}} \) (veh/km/lane) is the maximum density in the network. Thus, the non-metered outflow \( \hat{q}_o(k) \) is determined by the current origin demand if \( \hat{q}_{o,1}(k) < \hat{q}_{o,2}(k) \), or by the geometrically induced capacity \( Q_o \) if the mainstream density is undercritical, i.e., \( \rho_{\mu,1}(k) < \rho_{\mu,\mu} \), or
by the reduced capacity due to congestion of the mainstream if \( \rho_{\mu,1}(k) > \rho_{\text{cr},\mu} \). A similar approach applies to freeway-to-freeway (ftf) intersections.

Due to the complex nonlinear and dynamic nature of the macroscopic model, the factual critical density of a simulated freeway (at which the highest flow is observed) is not fully determined by the considered fundamental diagram (4). Thus, the freeway flow \( q_{\mu,1} \) in merge segments is maximized if the corresponding density \( \rho_{\mu,1} \) takes values around a factual critical density \( \rho_{\text{cr},\mu} \) which may be determined via simulations.

Freeway bifurcations and junctions (including on-ramps and off-ramps) are represented by nodes. Traffic enters a node \( n \) through a number of input links and is distributed to the output links according to the following equations:

\[
Q_n(k) = \sum_{\mu \in I_n} q_{\mu,n}(k) \tag{10}
\]

\[
q_{m,n}(k) = \beta^m_n(k) Q_n(k) \quad \forall m \in O_n \tag{11}
\]

where \( I_n \) is the set of links entering node \( n \), \( O_n \) is the set of links leaving \( n \), \( Q_n(k) \) is the total traffic volume entering \( n \) at period \( k \), \( q_{m,n}(k) \) is the traffic volume that leaves \( n \) via outlink \( m \), and \( \beta^m_n(k) \) (the turning rates) is the portion of \( Q_n(k) \) that leaves \( n \) through link \( m \).

If a node \( n \) has more than one leaving links, then the upstream influence of density is taken into account in the last segment of the incoming links by an appropriate calculation of \( \rho_{m,N_{n,i+1}} \) which is required in (3) for \( i = N_{n,i} \). If a node \( n \) has more than
one entering links, then the downstream influence of speed is taken into account by
appropriately calculating $v_{m,o}$ required in (3) for $i = 1$ (see Messmer and Papageorgiou,
1990, for more details).

The investigations reported in this paper are based on turning rate information rather
than OD information which is a modeling simplification. Note that AMOC can deal
with OD information (Kotsialos et al., 2002b), but at the expense of a considerably
increased computation effort due to the more detailed description of the traffic process.

3. Formulation of the optimal control problem

The coordinated ramp metering control problem is formulated as a discrete-time
dynamic optimal control problem with constrained control variables over a given
optimization horizon $K_p$, which can be solved very efficiently even for large-scale
networks by a suitable feasible-direction algorithm (Papageorgiou and Marinaki, 1995).
Thus, the freeway traffic flow is considered as the process under control via the various
ramp meters installed at the network entrances. The state of the process is described by
the state vector $x \in \mathbb{R}^N$ and its evolution depends on the system dynamics and the input
variables. Input variables are distinguished into control variables $u \in \mathbb{R}^M$ and external
disturbances $d \in \mathbb{R}^D$.

A general problem formulation will be introduced in the following. Note that the value
of each control variable may change less frequently than at each model time step $T$.
Assume that $M$ different control variables have $p$ distinct control sample times which
are multiples of the model sample time $T$, i.e., $T_l = z_l T$, $z_l \in \mathbb{N}$, $l = 1,2,\ldots,p$,
$p \leq M = \dim(u)$. Let $k_i = \lfloor k / z_i \rfloor$ and $u_i$ denote the vector of all control measures
that have sample time $T_i$. Then, $\mathbf{u}(k) = \left[ \mathbf{u}_i(k_i)^T \ldots \mathbf{u}_p(k_p)^T \right]^T$. The general discrete-time formulation of the optimal control problem is the following:

$$\min_{\mathbf{u}, \mathbf{x}} J = \varphi[\mathbf{x}(K_p)] + \sum_{k=0}^{K_p-1} \varphi[\mathbf{x}(k), \mathbf{u}_i(k_i), \ldots, \mathbf{u}_p(k_p), \mathbf{d}(k)]$$

subject to

$$\mathbf{x}(k+1) = \mathbf{f}[\mathbf{x}(k), \mathbf{u}_i(k_i), \ldots, \mathbf{u}_p(k_p), \mathbf{d}(k)], \quad \mathbf{x}(0) = \mathbf{x}_0$$

$$\mathbf{u}_{\text{min,}\ell} \leq \mathbf{u}_i(k_i) \leq \mathbf{u}_{\text{max,}\ell}, \quad \ell = 1, 2, \ldots, p$$

where $\varphi$ and $\varphi$ are twice differentiable nonlinear cost functions.

The state equation (13) can be deduced from the equations introduced in section 2. In this case, vector $\mathbf{x}$ consists of the densities $\rho_{m,i}$ and mean speeds $v_{m,i}$ of every segment $i$ of every link $m$ as well as the queues $w_{o,i}$ of every origin $o$. The control vector $\mathbf{u}$ consists of the ramp metering rates $r_{o,i}$ of every on-ramp $o$ under control, with $r_{\text{min,}o} \leq r_{o,i} \leq 1$. It is assumed that all ramp meters have the same sample time $T_i = z_i T$.

Finally, the disturbance vector $\mathbf{d}$ consists of the demands $d_{o,i}$ at every origin of the network and the turning rates $\beta_{m,o}$ at the network's bifurcations. The initial state $\mathbf{x}(0)$ and the disturbance trajectories $\mathbf{d}(k)$ over the time horizon $K_p$ must be known for a proper problem formulation. For practical applications, these values may be predicted more or less accurately based on historical data and real-time estimations (Wang et al., 2006).
The chosen cost criterion is the Total Time Spent (TTS) of all vehicles in the network (including the waiting time experienced in the ramp queues) which is a natural objective for the traffic system considered. The maximum ramp queue constraints may be taken into account via the introduction of penalty terms in the cost criterion penalizing queue lengths larger than \( w_{\text{max},o} \), which is a pre-determined maximum admissible queue for origin \( o \). Another penalty term may be added in order to suppress high-frequency oscillations of the optimal control trajectories. More precisely the cost criterion is the following

\[
J = T \sum_{k=1}^{K_P-1} \sum_{m=1}^{M} \rho_{m,i}(k) L_{m,i} \Lambda_{m} + T \sum_{k=1}^{K_P-1} \sum_{o} w_{o}(k) \\
+ T \sum_{k=1}^{K_P-1} \sum_{o} \alpha_{f} \left[ r_{o}(k) - r_{o}(k-1) \right]^2 + \sum_{k=1}^{K_P-1} \sum_{o} \alpha_{w} \left[ \max \{0, w_{o}(k) - w_{\text{max},o} \} \right]^2
\]  

(15)

where \( \alpha_{f} \) and \( \alpha_{w} \) are weighting factors.

The solution determined by AMOC consists of the optimal ramp metering rate trajectories \( u(k) \) and the corresponding optimal state trajectory \( x(k) \) over the optimization horizon \( K_P \).

4. **Hierarchical control**

The solution provided by AMOC is of an open-loop nature, i.e. it does not make use of measurements during the horizon \( K_P \), other than the initial state \( x(0) \). As a consequence, its direct application over the whole horizon \( K_P \) may lead to real traffic states that are increasingly diverging from the calculated optimal ones due to errors associated with the initial state estimate, the prediction of the disturbances, the model
parameters used and the existence of unpredictable incidents in the network. A receding-horizon (model-predictive control) approach can be employed to address to a certain degree any mismatch between the predicted and the actual system behavior. This approach is further extended, for even higher control robustness, to the hierarchical control structure shown in Figure 2 which consists of three control layers (Kotsialos 2004).

The Estimation/Prediction Layer receives as input historical data, information about incidents and real-time measurements from sensors installed in the freeway network. This information is processed in order to provide the current state estimate and the predictions of the future disturbances to the next layer. Within the proposed framework, the problem of demand prediction can be addressed by various available approaches (e.g., Lin, 2001; Okutani and Stephanedes, 1984; Smith et al., 2002).

The Optimization Layer (AMOC) considers the current time as the initial point \( k = 0 \) and the current state estimate as the initial condition \( x(0) = x_0 \). Given the predictions \( d(k), k = 0, \ldots, K_p - 1 \), the optimal control problem is solved delivering the optimal control trajectory (translated into optimal on-ramp outflows) and the corresponding optimal state trajectory. These trajectories are forwarded as input to the decentralized Direct Control Layer that has the task of realizing the suggested policy. As mentioned earlier, AMOC’s usage within the Optimization Layer is cast in a model-predictive (repetitive) control mode, whereby optimal results are produced each time over the time-horizon \( K_p \), but only the first part of these results are actually applied, after which the optimal results are re-calculated and so forth. More specifically, the update period or application horizon of the model-predictive control is \( K_A \leq K_p \) (to avoid myopic
actions), after which the optimal control problem is solved again with updated state
estimation and disturbance predictions. Thus the, originally open-loop, optimal control
problem is cast in a feedback control structure, since each new optimization run starts
with the real (estimated) state $x(0)$, due to which any previous modeling or prediction
errors are rejected. Quite naturally, the control actions have the tendency to be more
efficient with increasing $K_r$ and decreasing $K_A$. Note, however, that the feedback loop
associated with the model-predictive application mode may not be sufficient to reject
the impact of persistent errors, such as the mentioned mismatch between the model and
the real (uncertain) highway capacity. For example, if demands are higher than
predicted, then unnecessary queues may be created at some ramps while there are still
capacity reserves on the mainstream; on the other hand, if demands are lower than
predicted, it may not be necessary to meter in the main bottleneck area as strongly as
suggested by AMOC, i.e. some unnecessary ramp queue delays might be avoidable.
Furthermore, if the mainstream capacity is higher than predicted, then the direct
application of AMOC ramp flows may lead to a corresponding underutilization of the
real mainstream capacity; on the other hand, in case of capacity overestimation, a
mainstream congestion may be created via the AMOC ramp flows. Therefore, the
introduction of a sub-ordinate *Direct Control Layer* (Figure 2) is proposed, which
attempts to actually establish capacity flow at those mainstream locations where AMOC
asks for capacity flow; and to actually realize the AMOC-required traffic conditions on
all other mainstream locations (despite the potential demand or model mismatch).

For each metered on-ramp $o$ with merging segment $(\mu, 1)$ (Figure 1), a local regulator
can be applied with control sample time $T_c = z_c T$, $z_c \in \mathbb{N}$, (e.g., $T_c = 3T = 30s$) in order
to calculate the controlled on-ramp outflow \( q'_o(k_e) \) for the next control interval. The purpose of using \( r \) as a superscript in \( q'_o(k_e) \) is to differentiate the on-ramp’s outflow calculated by the local regulator from the outflow calculated from the maximum queue considerations (Eq. (19)) (the latter will be indicated with the use of \( w \) as a superscript).

The average quantities (over a control period) \( \overline{\rho}_{\mu,1}^*(k_e) = \frac{\sum_{z=1}^{k_e-1} \rho_{\mu,1}^*(z)/z_e}{1} \), \( \overline{q}_{\mu,1}^*(k_e) = \frac{\sum_{z=1}^{k_e-1} q_{\mu,1}^*(z)/z_e}{1} \) and \( \overline{q}'_{\mu,1}^*(k_e) = \frac{\sum_{z=1}^{k_e-1} q'_{\mu,1}^*(z)/z_e}{1} \), are defined, where the *-index denotes optimal values delivered by AMOC.

Two cases are distinguished for later comparison. In the first case, referred to as AMOC Rolling Horizon in the sequel, the optimal control trajectories (i.e., the optimal ramp outflows) are directly applied to the traffic process, that is,

\[
q'_o(k_e) = \overline{q}'_{\mu,1}^*(k_e). \tag{16}
\]

In the second case, the Direct Control Layer is actually introduced. Regulators ALINEA (Papageorgiou, et al., 1991) or flow-based FL-ALINEA (Smaragdis and Papageorgiou, 2003) are employed as local regulators, while the optimal state trajectory is used to determine the related set-points for each controlled on-ramp. It is recalled that the ALINEA local regulator with set-point \( \bar{\rho}_{\mu,1} \) reads

\[
q'_o(k_e) = q'_o(k_e - 1) + K_e \left[ \bar{\rho}_{\mu,1} - \rho_{\mu,1}(k_e) \right] \tag{17}
\]

where \( K_e > 0 \) is the feedback gain factor; while the flow-based FL-ALINEA with set-point \( \bar{q}_{\mu,1} \) reads
where $K_f > 0$ is the feedback gain factor. Thus, ALINEA (17) targets a mainstream density set-point $\tilde{\rho}_{\mu,1}$ while FL-ALINEA (18) targets a mainstream flow set-point $\tilde{q}_{\mu,1}$.

The flows $\tilde{q}_{\mu,1}$ are preferable as set-points for local regulation because they are directly measurable without the uncertainty caused by modeling; in other words, by targeting the density $\tilde{\rho}_{\mu,1}$ in the local regulator may not lead to the corresponding optimal flow $\tilde{q}_{\mu,1}$ due to possible related AMOC model errors. However, flows do not uniquely characterize the traffic state, as the same flow may be encountered under non-congested or congested traffic conditions. Moreover, whenever AMOC optimal results indicate capacity flow at specific ramp-merge areas, the corresponding flow set-point would be equal to AMOC’s flow capacity value; as it was already mentioned, however, the real flow capacity in a merge area may vary quite substantially from day to day while the critical density (or occupancy), at which capacity flow occurs, seems to be more stable (Keen et al., 1986; Elefteriadou et al., 1995; Lorenz and Elefteriadou, 2001; Cassidy and Rudjanakanoknad, 2005; Papageorgiou et al., 2006). For these reasons, a flow set-point $\tilde{q}_{\mu,1} = \tilde{q}_{\mu,1}^* (k_i)$ is used (in conjunction with FL-ALINEA), only if $\tilde{\rho}_{\mu,1}^* (k_i) \leq \rho_{f-cr,\mu}$ and $\tilde{q}_{\mu,1}^* (k_i) \leq 0.9q_{cap,\mu}$, i.e., only if the optimal flows are well below the critical and congested traffic conditions. If $\tilde{\rho}_{\mu,1}^* (k_i) \geq \rho_{f-cr,\mu}$ and $\tilde{q}_{\mu,1}^* (k_i) \leq 0.9q_{cap,\mu}$, then the AMOC optimal results tolerate an overcritical traffic state, and hence ALINEA is applied with set point $\tilde{\rho}_{\mu,1} = \tilde{\rho}_{\mu,1}^* (k_i)$; in all other cases, ALINEA with $\tilde{\rho}_{\mu,1} = \rho_{f-cr,\mu}$ is applied in order to guarantee maximum mainstream flow even in presence of various
model-parameter or disturbance-prediction mismatches (including the uncertain highway capacity). Finally, whenever the on-ramp queue calculated by AMOC is equal to zero, ALINEA with $\rho_{\mu,1} = \rho_{f,cr,\mu}$ is applied in order to guarantee that the real demand arriving at the ramp will be allowed to enter the freeway; this is done in order to avoid cases where an underestimation of the demand in AMOC would lead to an on-ramp flow that is lower than the one that the network can accommodate, thus leading to a ramp queue and corresponding driver delays without a real reason.

Whatever the employed local ramp metering strategy (16) or (17) or (18), the created ramp queues $w_o$ may exceed the corresponding allowed upper limits $w_{\text{max},o}$. Creation of excessive ramp queues can be avoided with the application of a queue control policy (Smaragdis and Papageorgiou, 2003) in conjunction with any local metering strategy (16)-(18). The queue control law takes the form

$$q_o^* (k) = -\frac{1}{T_o} \left[ w_{\text{max},o} - w_o (k) \right] + d_o (k, -1).$$

(19)

The final on-ramp outflow is then

$$q_o (k) = \max \left\{ q_o^* (k), q_o^r (k) \right\}.$$  

(20)

The calculated $q_o (k)$ is bounded by the maximum ramp flow $Q_o$ and a minimum admissible ramp flow $q_{\text{min},o}$. In order to avoid the wind-up phenomenon, the term $q_o^r (k, -1)$ used in both (17) and (18) is bounded accordingly.
5. Application results

5.1. The Amsterdam network

For the purposes of this study, the counter-clockwise direction of the Amsterdam ring-road A10, which is about 32 km long, is considered. There are 21 on-ramps on this freeway, including the ftf junctions with the merging freeways A8, A4, A2 and A1; and 20 off-ramps, including the connections with A8, A4, A2 and A1. The topological network model may be seen in Figure 3. The model parameters for this network were determined from validation of the network traffic flow model against real data (Kotsialos, et al., 2002a). The ring-road has been divided into 76 segments with average length 421m. This means that the state vector is 173-dimensional (including the 21 on-ramp queues). The disturbance vector is 41-dimensional (21 on-ramp demands and 20 off-ramp exit rates) while the dimension of the control vector is equal to the number of controlled on-ramps.

5.2. The no-control case

Using real (measured) time-dependent demand and turning rate trajectories as input to the METANET simulator without any control measures, heavy congestion appears in the freeway and large queues are built in some on-ramps. The density evolution and the corresponding queue profile are displayed in Figure 4. The excessive demand, coupled with the uncontrolled entrance of the drivers into the mainstream, causes congestion shortly after the beginning of the time horizon (Figure 4a). This congestion originates at the junction of A1 with A10 and propagates upstream, blocking A4 and a large part of the A10-West. After this congestion is partially dissolved, a new one appears and propagates upstream until it reaches the first congestion whose trend of resolving is
thereby reversed leading to a single more severe congestion. This strong congestion keeps the A4 entrance to the A10 blocked, which results in the accumulation of many vehicles at the ftf on-ramp of A4, with a queue that exceeds 1200 veh (in real life the congestion spills back onto A4 itself), and at the surrounding on-ramps (Figure 4b). The TTS for this scenario is equal to 14167 veh·h. The described no-control simulation results are very similar to the corresponding real traffic conditions (Kotsialos, et al., 2002a).

For the rest of this study, different control scenarios, introduced in Table 1, will be considered. In scenario 1, both urban and ftf on-ramps are controlled, but no maximum queue constraint is considered. For all other scenarios, when urban on-ramps are controlled, the admissible ramp queue $w_{\text{max,\ o}}$ is set equal to 30 veh as the urban ramp storage capacity is limited (scenarios 2-6). In scenarios where ftf on-ramps are controlled, different values for the admissible ramp queues are considered according to Table 1.

5.3. Application of ALINEA

ALINEA may be used at each ramp as a stand-alone strategy without any kind of coordination. The set-point for each controlled on-ramp $o$ is set equal to the factual critical density of the corresponding link $\mu$, i.e., $\tilde{\rho}_{\mu,\ o} = \rho_{\mu,\ o}$, in order to maximize the local freeway throughput. By simulation checking, this factual critical density was found to be roughly equal to $1.1\rho_{\mu,\ o}$.

All control scenarios presented in Table 1 were examined. Application of ALINEA to all the on-ramps without queue constraints (scenario 1) leads to a significant
amelioration of the traffic conditions, and the TTS is reduced to 7563 veh·h, which is an improvement of 47% compared to the no-control case. The related density evolution and the corresponding queue profile are displayed in Figure 5. The density profile is flat which demonstrates ALINEA’s efficiency as a local regulator. The critical point, however, is in the queue profile, where it may be seen that a huge queue is formed at the A1 ftf on-ramp, which actually prevents A1’s demand from triggering the congestion at the junction of A1 with A10. In fact, from Figure 4a it may be seen that, when no control is applied, both observed congestions are initiated at this critical junction. ALINEA keeps a suitable portion of A1’s demand out of the freeway for as much and as long as necessary, maintaining the downstream traffic density around the critical density. Thus, when ramp queue constraints are ignored, the ALINEA strategy is capable of creating excellent traffic conditions in the freeway, despite the fact that it operates in an uncoordinated fashion, but this happens at the expense of the drivers that wish to enter the freeway from A1, which renders this approach strongly unfair towards these drivers. Moreover, a long created ramp queue (Figure 5b) is likely to cause serious traffic problems upstream of the ramp.

When scenario 2 is considered, urban on-ramps are controlled and the maximum queue constraint (19) and (20) is active with an admissible ramp queue $w_{\text{max,}\text{r}}$ equal to 30 veh, while no control measure is applied to the ftf on-ramps. The related density evolution and the corresponding queue profile are displayed in Figure 6. ALINEA becomes much less efficient in this case and the resulting TTS is 13394 veh·h. Large queues are formed on A4 due to congestion (like in the no-control case of Figure 4b) reaching 1200 veh. The reason for this strongly reduced efficiency is quite clear; each independent ALINEA can only react to the mainstream congestion when the latter reaches its area;
however, even then, the limited ramp storage prevents ALINEA from dissolving the
congestion that propagates to the next upstream ramp and so forth.

When ALINEA is applied to the ftf on-ramps as well with an admissible ramp queue
equal to 200 veh (scenario 4), then TTS is reduced to 11517 veh·h. The related density
evolution and the corresponding queue profile are displayed in Figure 7. The control
efficiency in this case is clearly improved (over scenario 2) due to more available ramp
storage space, but the density profile indicates that the congestion is not resolved,
mainly due to the limitation of the A1 ftf on-ramp which may be seen in Figure 7b to
reach its maximum for almost the entire simulation horizon. This leads to a freeway
congestion creation at the A1 ramp that travels upstream, leading to the spreading of
ramp queues in the critical area between the junctions of A1 and A4 with A10 (southern
part of the ring). Note that large queues cannot be avoided on A4 also in this scenario,
reaching a maximum of 935 veh.

It is known that the introduction of queue constraints renders the control strategy more
equitable but also less efficient (Kotsialos and Papageorgiou, 2004). It has also been
noted in various studies (e.g., Zhang and Levinson, 2004) that the most efficient way for
conducting ramp metering is to impose strict control at the on-ramps close to the critical
area where congestion first occurs, which may be at the expense of equity. Therefore a
proper balance must be observed between both properties, that is, efficiency and equity.
In order to assess equity properties, Figure 8 depicts the average time spent by a vehicle
in each ramp queue plus traveling 6.5 km downstream on the freeway; for the no-
control case and the ALINEA strategy applied for scenarios 1 and 4. It can be observed
that in the no-control case the mean travel time is large at the A10-West as a direct
consequence of the created congestion. Without queue control (scenario 1) ALINEA reduces the mean travel time for all on-ramps but for A1, where a large peak appears due to extended delays in the on-ramp queue (Figure 5b). The introduction of the queue constraints (scenario 4) for ALINEA reduces the mean travel time at A1 but leads to travel time increases in other upstream on-ramps of A10-South and A10-West, mainly due to the created congestion (Figure 7a). The largest peaks are observed at the on-ramps A4, A2 and A1, which have the largest storage capacity. This is a more equitable distribution of the ramp delays required for the amelioration of the traffic conditions but, as expected, a less efficient one compared to scenario 1.

TTS values are plotted in Figure 9 for different admissible ramp queues at the ftf on-ramps. When urban on-ramps are not controlled (no-control case and scenarios 7-10), TTS values are higher compared to those obtained when urban on-ramps are controlled (with an admissible ramp queue equal to 30 veh). However, both trajectories converge towards the (dotted) TTS value that would have been achieved by ALINEA if the storage capacity of all ramps was infinite (scenario 1). Figure 9 demonstrates that ALINEA becomes increasingly efficient (but also increasingly unfair) as the available ftf ramp storage space increases.

5.4. Application of AMOC

The optimal open-loop solution, under the assumption of a perfect model and perfect information with respect to the future disturbances for the entire simulation horizon, serves as an "upper bound" for the achievable efficiency of the hierarchical control strategy (and in fact, of any ramp metering strategy) as it relies on ideal conditions. The resulting TTS for scenario 2, where only the urban on-ramps are controlled, is 11005
veh·h, which is an improvement of 22% compared to the no-control case. The related
density evolution and the corresponding queue profile are displayed in Figure 10. It is
obvious that, even with perfect knowledge of the disturbances, congestion cannot be
avoided (due to limited ramp storage space) and the queue at the A4 ftf on-ramp due to
the mainstream congestion now reaches 750 veh.

The resulting TTS for scenario 4, where both the urban and the ftf on-ramps are
controlled, is reduced to 7073 veh·h, which is an improvement of 50% compared to the
no-control case. This is of course, as mentioned above, an "upper bound" for the
efficiency of the hierarchical control strategy. The related density evolution and the
corresponding queue profile are displayed in Figure 11. It can be observed that the
formed queues at the ftf on-ramps are within the prescribed bounds of the scenario (200
veh). Note also the relatively equitable ramp queue distribution thanks to the imposed
queue constraints similarly to the ALINEA application. AMOC is able to anticipate the
creation of the congestion and it counters its cause by creating queues to the extent,
location and duration necessary, along with the respect of the imposed queue
constraints. Its anticipatory behavior, as opposed to the reactive nature of ALINEA,
deals with the causes of the problem before their consequences are manifested.
Remarkably, when, e.g., the A4 ramp is metered, the created ramp queue is much
shorter than when no metering is applied (as in no-control or in scenario 2).

TTS values are plotted in Figure 12 for different admissible ramp queues at the ftf on-
ramps. When urban on-ramps are not controlled (no-control case and scenarios 7-10),
TTS values are higher compared to those obtained when urban on-ramps are controlled
(with an admissible ramp queue equal to 30 veh). Again, both trajectories converge
towards the (dotted) TTS value that would have been achieved by AMOC open-loop strategy if the storage capacity of all ramps was infinite (scenario 1). A comparison of Figure 9 and Figure 12 reveals that AMOC open-loop is substantially more efficient than independent local ALINEAs under the same available ramp storage space. In other words, ALINEA calls for more ramp storage space to reach comparable efficiency as AMOC open-loop.

5.5. Application of hierarchical control

As mentioned above, results obtained by the optimal open-loop solution are not realistic because the assumption of perfect knowledge of the future disturbances cannot hold in practice. The proposed hierarchical control is able to cope with this problem by employing the rolling horizon technique, e.g., with $K_p = 360$ (1 hour) and $K_d = 60$ (10 min), i.e., optimal control results are calculated each time over a future horizon $K_p$ of 1 hour, and are updated (re-calculated) every $K_d$ of 10 min. It is assumed that the state of the system is known exactly when AMOC is applied every 10 min, which is a fairly realistic assumption. With respect to the prediction of the on-ramp demands and the turning rates, it is assumed that a fairly good predictor is available so that the smoothed real trajectories are used as the predicted ones (less favorable predictions will be investigated later). Figure 13 depicts an example of the actual and the predicted demand for the A1 ftf on-ramp. Similarly, Figure 14 depicts an example of the actual and the predicted turning rate (exit rate) for the A2 off-ramp. Finally, it is assumed that there is no mismatch between the model parameters used by METANET and the corresponding parameters used by AMOC and that there are no incidents in the network.
As mentioned in section 4, there are two cases for the application of AMOC results. In the first case, i.e. the AMOC Rolling Horizon case, the optimal ramp outflows calculated by AMOC are directly applied to the traffic flow process. The resulting TTS for scenario 4 is then 7422 veh·h, which is an improvement of 47.6% compared to the no-control case and 4.9% worsening compared to the optimum open-loop control. In the second case, the ALINEA and the FL-ALINEA strategies are employed (Direct Control Layer in Figure 2) and the resulting TTS for scenario 4 is 7399 veh·h, which is an improvement of 47.8% compared to the no-control case and 4.6% worsening compared to the optimum open-loop control. The related density evolution and the corresponding queue profile are displayed in Figure 15.

Apparently, there is no significant improvement of the TTS value when employing the Direct Control Layer compared to the first case (without Direct Control Layer). This is because the smoothed real trajectories are used as the predicted ones, which is a fairly good prediction. When uniformly underestimated or overestimated smoothed trajectories are used as the predicted ones, the superiority of the second case (with the Direct Control Layer) becomes more apparent as shown in Figure 16 which displays the obtained TTS for each strategy under scenario 4 when a uniform demand prediction error of up to ±10% is assumed. Note that uniformly positive or negative demand prediction errors is a rather unfavorable assumption for the control performance. Figure 16 also includes a horizontal line representing the TTS obtained by ALINEA for the same scenario; of course this TTS value does not depend on the % error of the demand prediction as ALINEA, due to its reactive nature, needs no prediction at all. Figure 16 demonstrates that the proposed hierarchical control structure reduces the sensitivity of the control results with respect to disturbance prediction errors, as compared with the
AMOC Rolling Horizon results without Direct Control Layer; and that both strategies
remain clearly better than ALINEA under this scenario even in case of substantial and
uniform demand prediction errors.

A similarly unfavorable assumption was introduced to investigate more directly the
impact of the highway capacity uncertainty. More specifically, the free speed parameter
in (4) was increased or decreased in AMOC by up to ±10%, which leads to an identical
change of the modeled AMOC highway capacity compared to the capacity of the
METANET simulator. Figure 17 demonstrates that, thanks to the introduced Direct
Control Layer regulators, the control sensitivity to capacity mismatches is moderate and
lower than in the case without that layer. The only exception is observed for a 10%
overestimation of the capacity used in AMOC. By closer inspection of this case, the
optimal ramp flows calculated by AMOC are higher than they should be based on the
real capacity. Without the Direct Control Layer, these flows are directly applied to the
traffic flow process leading to limited local congestion while the ramps are not fully
utilized and hence their storage space remains available for later use. On the other hand,
the introduction of the Direct Control Layer leads to an early utilization of the ramp
storage space, especially on A1, because the real capacity is indeed targeted through the
use of ALINEA with a set-point equal to the factual critical density. As a result, the
ramp storage space is not available when it is more urgently needed, i.e. during the
second half of the simulation horizon where congestion is indeed created leading to a
more substantial TTS increase than in the case without Direct Control Layer.

In conclusion, the utilization of the Direct Control Layer was found to usually improve
the control sensitivity with respect to demand prediction or model parameter errors, but
this does not exclude the possibility of individual deteriorations under specific constellations.

Returning to the density profile displayed in Figure 15a, there are no pronounced density peaks appearing. Thus, the hierarchical control strategy achieves the establishment of non-congested conditions in the freeway while respecting the maximum queue constraints (Figure 15b). Comparing the on-ramp queue evolution profile with the corresponding profile in the case of ALINEA (Figure 7b), the difference between both control strategies becomes apparent. In the ALINEA case, queues are built in the second half of the simulation horizon, in reaction to the congestion that has formed. In the hierarchical control case, the queues are built early in the simulation time in anticipation of the future congestion. Furthermore, this is done in such a manner that the maximum queue constraints are respected without serious degradation of the strategy's efficiency.

TTS values are plotted in Figure 18 for different admissible ramp queues at the ftf on-ramps. When urban on-ramps are not controlled (no-control case and scenarios 7-10), TTS values are again higher compared to those obtained when urban on-ramps are controlled (with an admissible ramp queue equal to 30 veh). However, this time the trajectories converge to each other already for admissible ftf queues equal to 200 veh (scenarios 4 and 8), at which point they virtually reach also the (dotted) TTS value that would have been achieved by the hierarchical control strategy if the storage capacity of all ramps was infinite (scenario 1).

When urban on-ramps are controlled (scenarios 2-6), TTS values for ALINEA, AMOC open-loop and the hierarchical control strategy are plotted for direct comparison in
Figure 19. It can be observed that, when ftf on-ramps are not controlled, then ALINEA and the hierarchical control strategy perform equally well; the uncontrolled strong inflows from the ftf on-ramps and the limited ramp storage capacity at the urban on-ramps do not allow for a more significant improvement over the no-control case. However, hierarchical control outperforms ALINEA when ftf on-ramps are controlled. Additionally, when the admissible ramp queue at the ftf on-ramps is equal to 200 veh, then the hierarchical control strategy virtually reaches the efficiency of the optimal open-loop solution while its efficiency remains the same for even larger values. On the other hand, ALINEA reaches a comparably high efficiency only if the available ftf ramp storage capacity is much higher.

Figure 20 depicts the average time spent by a vehicle in each ramp queue plus traveling 6.5 km downstream on the freeway, for the no-control case, the ALINEA strategy, the AMOC open-loop strategy and the hierarchical control strategy, the latter three applied with scenario 4 for the admissible ramp queues. In the hierarchical control case as well as in the AMOC open-loop case, the travel times are seen to be significantly lower than for the no-control case or ALINEA strategy for virtually all ramps. Clearly, the hierarchical controller's distribution of delays is performed in a more balanced way, which is more equitable for the drivers entering the mainstream at different ramps. Most importantly, travel times are (more or less significantly) reduced for virtually all ramps, hence no drivers have a reason to complain for the introduction of the ramp metering – quite the opposite.
6. Conclusions

Extensive simulation results of applying local feedback control, ideal open-loop control and rolling-horizon hierarchical coordinated control to the Amsterdam ring-road have been presented. Uncoordinated local control with ALINEA is quite successful in reducing the TTS and lifting congestion up to a certain degree depending on the imposed queue-length restrictions. However, congestion creation and spillback (e.g. on A4) are unavoidable in the realistically restricted cases. On the other hand, hierarchical control outperforms the uncoordinated local ramp metering approach if sufficient ramp storage can be made available.

In the network studied and for the specific disturbance profiles used, the introduction of ramp metering at some particular ramps within the network (the urban on-ramps) reduced some local traffic problems. However, a significant amelioration of the global traffic conditions in the network calls for comprehensive control of all ramps, including the ftf on-ramps, in the aim of optimal utilization of the available infrastructure. By building queues that do not exceed 200 veh on the ftf on-ramps, hierarchical control leads to a 47.8% improvement over the no-control case. What is equally important, the achieved high improvement level is quite robust even in view of prediction mismatch or uncertain highway capacity.

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8. References


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Figure Legends

Figure 1: The origin-link queue model.

Figure 2: Hierarchical control structure.

Figure 3: The Amsterdam ring-road.

Figure 4: No-control case: (a) Density profile; (b) Ramp queue profile.

Figure 5: ALINEA – Scenario 1: (a) Density profile; (b) Ramp queue profile.

Figure 6: ALINEA – Scenario 2: (a) Density profile; (b) Ramp queue profile.

Figure 7: ALINEA – Scenario 4: (a) Density profile; (b) Ramp queue profile.

Figure 8: Average travel time for queuing and traveling 6.5 km downstream for every on-ramp. ALINEA strategy applied for scenarios 1, 4.

Figure 9: TTS values when ALINEA strategy is applied with different admissible ramp queues at the ftf on-ramps.

Figure 10: AMOC Open-Loop – Scenario 2: (a) Density profile; (b) Ramp queue profile.

Figure 11: AMOC Open-Loop – Scenario 4: (a) Density profile; (b) Ramp queue profile.

Figure 12: TTS values when AMOC Open-Loop strategy is applied with different admissible ramp queues at the ftf on-ramps.

Figure 13: Real and predicted demand at the A1 ftf on-ramp.
Figure 14: Real and predicted turning rate at the A2 off-ramp.

Figure 15: Hierarchical Control – Scenario 4: (a) Density profile; (b) Ramp queue profile.

Figure 16: TTS values with respect to the % error on the demand prediction for different strategies when scenario 4 is applied.

Figure 17: TTS values with respect to the % error on the highway capacity used in AMOC for different strategies when scenario 4 is applied.

Figure 18: TTS values when Hierarchical Control strategy is applied with different admissible ramp queues at the ftf on-ramps.

Figure 19: TTS values when urban on-ramps are controlled with an admissible ramp queue equal to 30 veh. Different strategies applied and different admissible ramp queues at the ftf on-ramps.

Figure 20: Average travel time for queuing and traveling 6.5 km downstream for every on-ramp. ALINEA, AMOC Open-Loop and Hierarchical Control applied for scenario 4.
Tables

Table 1: Admissible ramp queues (veh) for urban and ftf on-ramps per scenario studied.

<table>
<thead>
<tr>
<th>Scenario</th>
<th>Admissible ramp queue for controlled urban on-ramps (veh)</th>
<th>Admissible ramp queue for controlled ftf on-ramps (veh)</th>
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<td>+∞</td>
</tr>
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</tr>
<tr>
<td>6</td>
<td>30</td>
<td>400</td>
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<tr>
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Figure 1
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