Fastlane

Traffic flow modeling and multi-class dynamic traffic management

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Abstract

Dynamic Traffic Management (DTM) aims to improve traffic conditions. DTM usually consists of two steps: first the current traffic is estimated, then appropriate control actions are determined based on that estimate. In order to estimate and control the traffic, a suitable traffic flow model that reproduces the properties of traffic well must be used. One of the most important properties is that traffic is composed of multiple vehicle classes. While many traffic flow models have been proposed and applied in DTM, most of them do not capture the dynamics of multiple vehicle classes.

In this paper, we propose a multi-class traffic flow model, Fastlane, that reproduces the dynamics and interactions of different vehicle classes. It is especially well-suited for short term multi-class traffic control on freeways. We show three applications of Fastlane: traffic state estimation, traffic state prediction and pro-active control.

Keywords

Traffic flow, Multi-class, Traffic management, State estimation, Model-predictive control
1 Introduction

Dynamic traffic management (DTM) aims to improve traffic flow conditions by means of control actuators on the basis of real-time information. Therefore, DTM has played a major role in solving traffic congestion. It requires online applicable and reliable systems to support its performance. Figure 1 schematically outlines such an ideal traffic control system, which usually performs three closely intertwined tasks. These tasks are (i) traffic state estimation (Wang & Papageorgiou, 2005; Yuan et al., 2012), in which data from various traffic sensors like inductive loops, cameras or probe vehicle reports, and online traffic flow models are used to reconstruct a network-wide picture of the traffic state, for instance in terms of traffic densities or speeds. These can in turn be used as a basis for (ii) traffic state prediction and (iii) traffic control. Examples of DTM measures are speed-limit control (Hegyi et al., 2005), ramp metering (Hegyi et al., 2005; Papamichail et al., 2010), and route guidance (Wang et al., 2003; Schreiter et al., 2012). This control system thus allows traffic managers to assess different traffic control and information provision scenarios in real-time. As a foundation, a suitable traffic flow model is required. This paper focuses on developing such an online traffic flow model and its applications for traffic state estimation, traffic state prediction and pro-active control in DTM.

Regarding traffic flow modeling, we consider an important perspective, namely driver and vehicle heterogeneity. Different vehicle classes have different characteristics, such as maximum speeds, vehicle lengths, reaction times, minimum distance headways, and so forth. Multi-class takes into account this heterogeneity. Most such models are car-following models, but since (Wong & Wong, 2002) many multi-class kinematic wave models have been developed. By including heterogeneities in modeling, these traffic flow models are not only able to describe traffic flow more accurately (Bellomo & Dogbe, 2011), but also the control applications for such models are more elaborate. This type of multi-class control is especially valuable in areas with high truck percentages.

Figure 1: The control loop for multi-class Dynamic Traffic Management.
Our main contribution is the presentation and application of a new multi-class first-order traffic flow model, Fastlane (First-order fAST muLti-class mAcroscopic traffic flow model for simulation of NEtwork-wide traffic conditions). First, the model is formulated in the Eulerian coordinate system which is fixed in space. We reformulate the model in the Lagrangian coordinate system which moves with the vehicles (Leclercq et al., 2007; Van Wageningen-Kessels et al., 2010). The new formulation has several advantages related to traffic state estimation and control. The model is in turn used for a series of online DTM applications, including short-term traffic prediction, online traffic state estimation and class-specific model predictive control (Figure 1). All the applications will be tested in a real traffic network: A15 in the Netherlands (Figure 2), which is an important freight-transport corridor connecting the harbor city of Rotterdam with the hinterland. We have chosen this location for two reasons. Firstly, there are high truck percentages (higher than 20% sometimes, refer to Figure 3). Secondly, a lot of data are available: dual-loop detectors are located at about every 500 m, providing 1-min aggregate flow and speed profiles, and video-recording data from helicopters and individual vehicle data at cross-sections are available at selected spatiotemporal dimension.

The paper is organized as follows. Section 2 first presents the mathematical definition of Fastlane in both Eulerian and Lagrangian coordinates. Section 3 addresses the application of Fastlane for short-term traffic prediction, where the calibration and validation of the model are explained. In Section 4, Fastlane is employed to estimate the current traffic states on freeway networks. On the basis of the validated Fastlane model and the current traffic estimates, a proactive multi-class traffic control approach is illustrated and tested in Section 5. Finally, the conclusions and further research are outlined.
2 Fastlane model

The Fastlane model is a multi-class extension of the LWR model (Lighthill & Whitham, 1955; Richards, 1956). It is based on the same principles, such as the conservation of vehicles and the assumption that traffic is always in equilibrium. The principles are complemented with the multi-class assumption: vehicles can be grouped into classes with similar characteristics. In this section we first introduce the model; secondly, we propose an alternative formulation. Finally, we discuss how the model equations can be discretized for application in computer simulations. The discretization and simulation methods will be applied in the following section discussing applications of Fastlane.

2.1 Model development

The Fastlane model consists of $U$ conservation equations, $U$ fundamental relations and two equations to couple both. $U$ denotes the number of classes. The conservation equations are a multi-class generalization of the conservation equation in the LWR model:

$$\frac{\partial k_u}{\partial t} + \frac{\partial q_u}{\partial x} = 0 \quad (1)$$

with $k_u$ the density of class $u$ in $\text{veh km}^{-1}$ and $q_u = k_u v_u$ its flow in $\text{veh h}^{-1}$, with $v_u$ its speed in $\text{km h}^{-1}$. It is assumed that there are two regimes: free flow and congestion. In free flow the classes travel at different speeds; in congestion all classes have the same speed. Furthermore, in free flow, the velocity of cars, and possibly other classes, decreases. This results in the fundamental relation shown in Figure 4(a). The shape of the fundamental relation is in line with observations (Hoogendoorn, 1999, Chapter 8), (Smulders, 1990; Kerner & Rehborn, 1996; Helbing, 1997). It is important to note that the fundamental relation expresses the class specific speed $v_u$ as a function of the effective density $K$.

The definition of the effective density is characteristic for Fastlane and distinguishes it from other multi-class LWR models such as Wong & Wong (2002); Chanut & Buisson (2003); Ngoduy & Liu (2007); Logghe & Immers (2008). It takes into account that at low densities and high speeds, headways have a large impact on traffic flow, while at high densities and low velocities, vehicle lengths have a large impact on traffic flow. This observation has lead to the passenger car equivalent (pce) value illustrated in Figure 5. The pce value is in turn used to compute the effective density:

$$K_{\text{tot}} = \sum_u \pi_u k_u \quad (2)$$

with the pce function:

$$\pi_u(k) = \frac{l_u + h_u v_u(k)}{l_1 + h_1 v_1(k)} \quad (3)$$

with $l_u$ the length of vehicles of class $u$, $h_u$ their minimum headway and reference class $u = 1$ (usually passenger cars). Finally, we note that the model (1), (2), (3) with the fundamental relation as in Figure 4 is formed by an implicit set of equations which do not necessarily uniquely define the traffic state. Van Wageningen-Kessels (in progress) shows how to reformulate the model such that the equations uniquely define the traffic state, without changing the model itself.
The Fastlane model introduced above satisfies important requirements for multi-class models, if parameter values are within a reasonable range (Van Wageningen-Kessels et al., in press; Van Wageningen-Kessels, in progress). One of the requirements is anisotropy: characteristics do not travel faster than vehicles. A generalization of the Fastlane model is applied to assess other multi-class LWR models with respect to the same requirements. Van Wageningen-Kessels et al. (in press); Van Wageningen-Kessels (in progress) show that other models known from literature do not satisfy all requirements.

2.2 Reformulation in Lagrangian coordinate system

The Fastlane model is reformulated in the Lagrangian coordinate system. The Lagrangian coordinate system moves with the vehicles of class 1. Vehicles are numbered in opposite driving direction: the first vehicle gets number \( n = 1 \), the second \( n = 2 \), etc. The reformulated model describes the evolution of the spacing (5) over time and vehicle number. Figure 6 shows a control volume that can be used to derive the Lagrangian conservation equation. This results in the Lagrangian multi-class conservation of vehicles.
equations:

$$\frac{Ds_1}{Dt} + \frac{\partial v_1}{\partial n} = 0 \quad (4a)$$

$$\frac{Ds_u}{Dt} + u \frac{\partial v_u}{\partial n} + \frac{v_1 - v_u}{s_1} \frac{\partial s_u}{\partial n} = 0 \quad (4b)$$

with the spacing of class \( u \):

$$s_u = \frac{1}{k_u} \quad (5)$$

The definition of spacing (5) can be applied to reformulate the rest of the model (fundamental relation (see Figure 4(b)), effective density/spacing and pce function) in Lagrangian coordinates. Van Wageningen-Kessels et al. (2010) show in more detail how the model can be derived.

Some of the advantages of the newly formulated model are based on the fact that in the Lagrangian formulation characteristics (information) always travels in one direction: from one vehicle to its follower and never in the opposite direction. This can be understood intuitively by considering two vehicles. If the leader brakes or accelerates, the follower will react to this. However, if the follower changes its velocity, the leader will not react. The Lagrangian formulation results in less nonlinear model equations which are easier to discretize (see Section 2.3) and to apply in, for example, Kalman filtering (see Section 4). The advantages of the Lagrangian formulation are:

1. more efficient traffic state estimation (Yuan et al., 2012)
2. faster and more accurate traffic state prediction and control
3. simpler model analysis (eg. for anisotropy)
4. simpler coupling with microscopic models to form hybrid (macro-micro) models
5. simpler adaptations and extensions of the model such as bounded acceleration

The last two advantages, for mixed class models in Lagrangian formulation, are discussed in Leclercq (2007, 2009).

2.3 Discretization and nodes

To apply the Fastlane model in a computer simulation, the model needs to be discretized. Van Lint et al. (2008a) propose a discretization of the Fastlane model in Eulerian coordinates. In fact, it is an adaptation of the minimum supply demand method for multi-class models. For the discretization of the model in Lagrangian coordinates the upwind method is adapted. Time is divided into time steps \( \Delta t \) of usually a few seconds. Vehicles of class 1 are grouped into groups of \( \Delta n \) vehicles. Since we are dealing with a continuum model and are not interested in the dynamics of individual vehicles, \( \Delta n \) can take any positive value: it is not necessarily an integer. At each time step the position of each vehicle group is calculated. Furthermore, the class specific spacings \( s_u \) of each user class at each time step and at each vehicle group is calculated. For the discretization of the Lagrangian conservation equation (4) a first order upwind method
(a) Vehicle trajectories (curved lines) and a control volume that follows a platoon of $\Delta n$ vehicles over a time $\Delta t$. The final length $(s_2 \Delta n)$ is the initial length $(s_1 \Delta n)$ plus the distance travelled by the first vehicle $(v_1 \Delta t)$ minus the distance travelled by the last vehicle $(v_2 \Delta t)$. Rewriting $s_2 \Delta n = s_1 \Delta n + v_1 \Delta t - v_2 \Delta t$ yields the Lagrangian conservation equation for class 1 (4a).

(b) Vehicle trajectories (solid lines: class 1, broken lines: class $u$) and a control volume. A platoon of $\Delta n$ vehicles of class 1 is followed over time $\Delta t$. The inflow of vehicles of class $u$ into the platoon $(s_1 \Delta n + v_1 \Delta t - v_1 u \Delta t)$ equals the outflow $(s_2 \Delta n + v_2 \Delta t - v_2 u \Delta t)$. Rewriting this yields the Lagrangian conservation equation for class $u$ (4b).

Figure 6: Vehicle trajectories and control volumes to derive the Lagrangian multi-class conservation equation.
Figure 7: Network model of the site; the width of each line indicates the number of lanes modeled, the stars indicate the location of the regular bottlenecks.

is applied:

\[
\begin{align*}
    s_{j+1}^{i,j} & = s_{1,i}^{j} + \frac{\Delta t}{\Delta n} \left( v_{1,i-1}^{j} - v_{1,i}^{j} \right) \tag{6a} \\
    s_{j+1}^{u,i} & = s_{u,i}^{j} - \frac{\Delta t}{\Delta n} \left[ s_{u,i}^{j} \left( v_{u,i}^{j} - v_{u,i-1}^{j} \right) + \frac{v_{1,i}^{j} - v_{u,i}^{j}}{s_{1,i}^{j}} \left( s_{u,i}^{j} - s_{u,i-1}^{j} \right) \right] \tag{6b}
\end{align*}
\]

with \( j \) the time step index and \( i \) the vehicle groups index (only referring to vehicles of class 1).

The discretization (6) is applied to homogeneous parts of the network. At nodes, such as ramps and locations where the number of lanes changes, a node model is applied. The node model describes how vehicle groups travel over nodes. This includes a bifurcation model including turnfractions or routes and a merge model including priority-taking (Van Wageningen-Kessels et al., 2011). The Lagrangian node model has been extended to multi-class nodes, however the method has not been published yet.

3 Application I: Short-term traffic prediction

The first application of Fastlane is to predict the traffic state of a freeway network short term. In Section 3.1, we calibrate the parameter values of Fastlane to the traffic conditions of the A15. Then, we show in Section 3.2 that Fastlane accurately predicts the traffic state under both regular and incidental conditions.

3.1 Calibration

A number of parameter values of Fastlane have to be specified so that it correctly predicts the traffic conditions of the A15.

Network model

The network layout is directly visible in areal maps, for example in the ones provided by [2]. Figure 7 shows the network modeled in Fastlane. The width of the lines indicates the number of lanes modeled, varying from one lane for most of the on- and off-ramps to four lanes between the on-ramp Charlois and the bottleneck Charlois. Each on-ramp is modeled as an origin-link, for which the inflow has to be calibrated. Each of the off-ramps is modeled as a destination-link, for which the turnfraction of the adjacent bifurcation node has to be calibrated.
Figure 8: Pce function dependent on the speed of trucks used in the prediction.

Inflows and turnfractions
Since the A15 is covered by many induction loops, the inflows and turnfractions of the on-ramps, off-ramps and junctions can be measured. We use historic data of one year and categorize them into the seven days of the week. In order to estimate the regular patterns and omit the influences of outliers caused by incidental conditions, we apply the median to the 52 data sets for each weekday. The resulting patterns are distributed to the vehicle-classes according to the observed truck percentage, resulting in class-specific inflows and turnfractions, respectively.

PCE function
We gathered videos by a helicopter camera to provide data about the relation between cars and trucks on the A15. Figure 9 shows a frame of such a video. Clearly visible are the different spacings between cars and trucks. Such videos are used to calibrate the parameter values of the pce function $\pi_{\text{truck}}$ (3); see Figure 8 for the result.

Figure 9: Frame of a video of the A15; trucks have a much larger spacing than cars.

Fundamental diagram
Since the capacity is only observable at active bottlenecks, we assume an effective capacity of $2250 \frac{\text{pce}}{h}$ per lane at non-bottleneck locations. The capacities of the recurrent
Table 1: Calibrated parameter values of the pce function and the fundamental diagram at non-bottlenecks.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Symbol</th>
<th>Calibrated value</th>
</tr>
</thead>
<tbody>
<tr>
<td>minimum spacing of cars</td>
<td>$s_{\text{min}}$</td>
<td>7 m</td>
</tr>
<tr>
<td>minimum headway of cars</td>
<td>$h_{\text{min}}^\text{car}$</td>
<td>1 s</td>
</tr>
<tr>
<td>minimum spacing of trucks</td>
<td>$s_{\text{min}}^\text{truck}$</td>
<td>25 m</td>
</tr>
<tr>
<td>minimum headway of trucks</td>
<td>$h_{\text{min}}^\text{truck}$</td>
<td>1 s</td>
</tr>
<tr>
<td>effective capacity per lane</td>
<td>$v_{\text{crit}}^\text{pce} \cdot k_{\text{crit}}^\text{pce}$</td>
<td>2250 pce h^{-1}</td>
</tr>
<tr>
<td>effective jam density per lane</td>
<td>$k_{\text{jam}}^\text{pce}$</td>
<td>143 pce km^{-1}</td>
</tr>
<tr>
<td>critical speed</td>
<td>$v_{\text{crit}}$</td>
<td>85 km h^{-1}</td>
</tr>
<tr>
<td>free speed cars</td>
<td>$v_{\text{free}}^\text{car}$</td>
<td>110 km h^{-1}</td>
</tr>
<tr>
<td>free speed trucks</td>
<td>$v_{\text{free}}^\text{truck}$</td>
<td>85 km h^{-1}</td>
</tr>
</tbody>
</table>

Bottlenecks have a large effect on the traffic conditions; we therefore calibrate them by an automatic optimization procedure based on 100 calibration data sets. The objective is to find the capacities in such a way that the predictions closely match the true traffic conditions. Specifically, the congestion has to be located at the right place and at the right time, i.e. the difference of the traffic regime between the prediction and the ground truth is minimized.

Summary

In summary, Fastlane is calibrated based on historic data. Table 1 lists the parameter values of Fastlane used for the A15. Most of the parameter values are determined by historic averages or rules of thumb. The capacities at the regular bottlenecks, however, are calibrated by an optimization procedure with the objective to place the predicted congestion at the right location and at the right time.

3.2 Validation

This section validates the model by comparing the prediction of Fastlane with the ground truth traffic state. The ground truth traffic state was estimated by applying a fast version (Schreiter et al., 2010) of the Adaptive Smoothing Method (Treiber et al., 2011) to the sensor data gathered by the induction loops of the A15. The model will be validated for both regular and incidental conditions. The data sets applied in the validation are disjoint from the data sets used to calibrate the capacities in the previous section.

3.2.1 Validation under regular conditions

The model is validated for the evening peak. We applied data of ten days, starting at four different times, resulting in forty data sets. Figure 10 shows the result of a data set. The ground truth (Figure 10(a)) shows that the regular bottlenecks at Km 56 (Charlois) and at Km 44 (Spijkenisse) were active so that congestion emerged there. Fastlane predicts both congestions at the right place, and also reproduces their growth as the demand during the evening peak grew (Figure 10(b)). The difference of traffic regimes
Figure 10: Validation of Fastlane under regular conditions (30-03-2011 at 15:30).

between the predicted and the ground truth state is shown in Figure 10(c). Integrating the absolute of the regime error leads to a value of 6.1 km h.

Out of the 40 validation data sets, 31 of them show a good match with reality, whereby six of them closely match the true traffic conditions. In nine cases, the prediction results were far off the true traffic conditions. In the latter cases, the bad predictions were probably caused by inflows and turnfractions that are far off the historic average values used in the prediction. A better estimation of those parameters would improve the prediction. Similarly, the capacity is a stochastic variable; an online calibration of the capacity would probably improve the prediction performance. Figure 11 shows the histogram of the validation of the data sets.
3.2.2 Validation under incidental conditions

Ten days where an incident occurred were selected as validation data sets. The location of the incident, the remaining capacity and the duration of it were fed into Fastlane.

Figure 12 shows the results for of a data set at 16:15 where an incident occurred at Km 41 and lasted until 16:40. As can be seen, the congestion caused by the accident is predicted accurately. Furthermore, when the accident clears, the resulting regular congestion emerging at Km 44 (Spijkenisse) is predicted well. (Note that the incident in the ground truth appears to be located further downstream. This is due to the finite acceleration of the vehicles, which need some hundreds of meters to accelerate to a high speed. This finite acceleration is not modeled in Fastlane where the vehicles immediately reach a high speed.) The difference of the predicted and the ground truth is 7.3 km h (Figure 12(c)).

Six out of the ten data were are predicted well, only one of them was far off, and three of them showed a mediocre prediction quality. The histogram in Figure 11 shows the validation results.

3.3 Discussion of short-term prediction

Fastlane predicts the traffic state of the A15 for the horizon of one hour. It is both able to predict traffic under regular conditions and under incidental conditions. For the latter, we showed an example of an accident; the congestion it caused was correctly predicted.

One direct application of the validated Fastlane model is the prediction of the traffic state, as shown in this section. Currently, the predictions for the A15 are performed online and the results can be viewed at BOS-HbR Homepage (2012). Furthermore, the validated model can be used in an recursive state estimator, which combines sensor data with the predictions of a traffic flow model, as it will be shown in the following section. Another application is proactive traffic control, where the control signals are determined based on the predicted traffic state. Section 5 shows such an application where the calibrated Fastlane model is used in an optimal control approach.
4 Application II: Traffic state estimation

This section presents the application of traffic state estimation on the basis of the Fastlane model formulated in the Lagrangian coordinate system. We first introduce the methodology of the application in traffic state estimation. Our reason for applying the Lagrangian formulation of the Fastlane model instead of the Eulerian formulation is elaborated. Then, an experimental study is set up to test and validate the state estimation approach on the real traffic network A15. In the experiment, different types of sensor data are incorporated. Finally, we further explore the advantages of this traffic state estimation approach, based on the results provided.

4.1 Methodology

In general, model-based state estimation consists of three elements (Figure 13). To compute and predict system state variables (e.g., density \(k\), speed \(v\) or spacing \(s\), dy-
Traffic State Estimation

Process model
- Lagrangian formulated Fastlane model

Observation model
- Multi-class Lagrangian fundamental relations

Data-assimilation method
- Extended Kalman Filter (EKF)

Figure 13: Structure of the traffic state estimation method.

Dynamic traffic flow models are used as the process model. So called observation models (i.e., fundamental diagrams) are used to compute and predict from these state variables the expected observations from traffic sensors. Finally, a data-assimilation technique is needed to estimate the most probable traffic states using both the model predictions and the actual sensor observations. Figure 13 also clarifies the choices made with respect to these three elements.

As the first element, the Lagrangian formulated Fastlane model is applied as the process model. The discretized formulation (6) constitutes the non-linear state-space traffic system model in Lagrangian coordinates. The multi-class Lagrangian node model extends the traffic system model to a network level. The related multi-class Lagrangian fundamental relations (see Figure 4(b)) can be used as the observation model.

For data assimilation, the Extended Kalman Filtering (EKF) technique is applied. Details about EKF in general can be found, for example, in (Haykin, 2001). This technique has been widely applied in real-time traffic state estimation with a certain success (Wang & Papageorgiou, 2005; Tampere & Immers, 2007; Van Lint et al., 2008b; Yuan et al., 2012). It outshines the other computational-expensive methods, such as the Unscented Kalman Filtering or the Particle Filtering, which require a significant number of process and observation model instances (samples) to run in parallel. The EKF is a one-shot process and thus suited for on-line applications, while maintaining reasonable estimation accuracy. Yuan et al. (2012) has also demonstrated that the (mixed-class) Lagrangian formulation of traffic state estimation outperforms its Eulerian counterpart in the EKF-based framework. This is due to the improvements in both the prediction step and the correction step of the data-assimilation method. In the former, the Lagrangian formulation leads to more accurate numerical simulation. In the latter, the non-mode-switching (mode: congestion or free-flow) numerical scheme (upwind scheme) is suitable for the linearization of the process model. In the Eulerian formulation, however, the derivative of the Eulerian model shows a sudden mode change around capacity (free-flow or congestion). Due to this mode-switching, the error in the Eulerian case may lead to EKF corrections with the “wrong” sign.

The main limitation of implementing the EKF method to a multi-class traffic system model is that the linearization or the derivation analysis of the system models may not be possible (Ngoduy, 2008). For instance, the linearization of the Eulerian Fastlane model is complex or even impossible, due to the additional interaction terms in the class-specific flux calculation. Nonetheless, the Lagrangian formulation of the Fastlane
model enables a relatively straightforward derivation analysis (the derivative of equations (6a) and (6b) with respect to the spacing of each user class) and makes it possible to apply an EKF approach for traffic state estimation. Therefore, the traffic state estimation applies the EKF technique rooted in the Lagrangian formulation of the Fastlane model.

4.2 Experimental setup

To test the Fastlane-based traffic state estimation, an experimental study was conducted based on the real traffic network A15 in the Netherlands. All the available observations from the A15 freeway were incorporated into the state estimation.

4.2.1 Data and test network

The data used in this experiment were obtained from the A15. The studied area was a part of the eastbound carriageway of the Dutch freeway A15 (a subset of the A15 used in the previous section). The studied time period covered the afternoon peak hours, from 14:00 to 20:00. The chosen road segment is about 8300 m in length, with the milepost A15R-50.53km to A15R-58.83km as illustrated by Figure 14. Most of the carriageways in this segment contains three vehicle lanes.

The fundamental parameters were calibrated from loop-detector data sets. During October of 2011, several selected detectors, with the mileposts A15R-51.83km, A15R-52.48km and A15R-55.12km, additionally collected individual vehicle data (IVD) so that class-specific data (speeds, vehicle lengths) are available. On 25th October 2011, a helicopter was used to collect vehicle trajectory data around the bottleneck segment (about 500 m in length, highlighted in Figure 14) within the study section during the afternoon peak (starting around 16:15). All the individual vehicle trajectory data (locations, reporting time stamps, vehicle lengths) can be extracted from video via image processing techniques (Knoppers et al., 2012). On the basis of these data, we can further interpolate vehicle speeds and vehicle classes, which can be used as detailed observation inputs. In addition, based on the data from the helicopter, we can calibrate some class-specific model parameters, such as driver reaction time and minimum dis-
Distance headway (e.g., $h_u$ and $l_u$ in equation (3)). In principle, the ground truth data are available for the segment covered by the helicopter camera; however, no ground truth information is available for the rest of the road stretch.

This freeway segment contains four on-ramps and one off-ramp, one in-flow and one out-flow boundary. The in-flow boundary starts from a loop detector, where the in-flow can be determined. Multi-class node models are used to deal with the network discontinuity.

### 4.2.2 Experimental scenarios

The purpose of this experiment is to validate the concept of applying the Lagrangian formulated Fastlane model for traffic state estimation by incorporating multiple observation data sources at a network level, and to explore its advantages. Since there are no ground truth data available on the studied A15 section (only for a small segment), this experiment addresses qualitative research.

The time step $\Delta t$ and the platoon size $\Delta n$ in the simulation were chosen as 2 (s) and 7 (veh.), respectively. This discretization choice was assumed to provide sufficient accuracy for this network application. All three types of observations from the chosen freeway segment (on 25th October 2011), namely aggregate loop data, IVD at selected locations and helicopter trajectory data, were input as observations. Several spatial resolutions of aggregate loops were investigated, namely around 500 m, 1000 m, and 1500 m apart. Table 2 overviews all the scenarios in this study. Generally, spacing observations are also not directly available from those spatially-fixed sensors but can be inferred under an assumption of the local homogeneous condition (speeds of vehicles are constant in a short time period). To demonstrate concepts, we only used speed observations from loops, IVD and trajectory data, and distinguished only two vehicle classes, namely cars and trucks.

<table>
<thead>
<tr>
<th>No. Sce. (3 x 1 x 2)</th>
<th>Resolution</th>
<th>Loop speed (class-specific)</th>
<th>IVD speed (class-specific)</th>
<th>Trajectories (class-specific)</th>
</tr>
</thead>
<tbody>
<tr>
<td>6</td>
<td>500m, 1000m, 1500m</td>
<td>Three loops</td>
<td>All included</td>
<td>Included or not</td>
</tr>
</tbody>
</table>

**Table 2: Experimental data scenarios on A15 for traffic state estimation.**

### 4.3 Results

The experiment presents qualitative analyses. As shown in Figure 15 with all the speed contour plots, all three data sources are successfully incorporated into the multi-class state estimator, providing adequate estimation results. Traffic network discontinuities are sufficiently modeled and simulated. One on-ramp (at 1155 m) and one off-ramp (at 2095 m) are clearly illustrated by two horizontal regions at the locations around 1000 m and 2000 m, respectively. The area between 4000 m and 5000 m is related to a weaving section of four lanes (lane expansion) on the A15. In cases 1 and 2, stop-and-go waves are clearly visible in the congested area. As the detection resolution decreases in cases 3 and 4, the performance is limited compared with the 500 m detection scenario.
Nonetheless, the basic traffic patterns and network discontinuities are reflected in the results.

The only difference between case 1 and case 2 is that case 2 additionally incorporates vehicle trajectory data as observation inputs. Comparing Figure 15(a) with Figure 15(b), it is difficult to differentiate the difference between the two cases. Therefore, we further illustrate the difference in speed estimates between these two scenarios in Figure 16. We notice that the estimate difference at certain spatiotemporal cells is even over 100%, and this difference is starting the moment the trajectory data are available as observations. Figure 15(b) indicates the region where the vehicle trajectory data were collected. These individual trajectories can be directly related to a vehicle (car or truck) platoon (discretized unit in the estimation model). For instance, the space mean speed observation for a vehicle platoon is determined by averaging all the speed samples within its range. As indicated, trajectory data generally provide more detailed information at the collection area compared to loop data. Hence, the estimates in case 2 (also in other cases using trajectory data) are expected to benefit from it.

One of the main advantages of multi-class state estimation is to provide class-specific traffic state estimates, such as speeds, densities, and flows. Figure 17 shows that speed estimates for both car and truck classes are available from simulations. The speed patterns of the two classes are similar to each other in congestion, whereas in the free-flow state truck speeds are bounded by a maximum value of about 85 km/h. Moreover, traffic compositions over space and time can be accordingly calculated from class-specific densities. As a result, people might monitor the share in total flows of each vehicle class over time at specific locations. Compared to the mixed-class raw-speed observations (Figure 17(a)), multi-class estimation offers more useful information, which is important for class-specific traffic control and management.

4.4 Discussion

This experiment has demonstrated that the state estimation method with the Lagrangian formulated Fastlane model successfully provides class-specific state estimates in a real freeway network (see Figure 17), using all types of traffic observations (in both the Eulerian and Lagrangian forms, in both the mixed-class and multi-class patterns). By implementing multi-class node models, the state estimator is extended to model network discontinuities and gives adequately good results. It provides the foundation of information for a wide range of class-specific control applications, which will be discussed further in the next section.

5 Application III: Proactive multi-class traffic control

The third application employs Fastlane in an proactive control approach, where the traffic conditions of the A15 are predicted, and optimizes the signals of multi-class DTM measures in order to minimize the total cost of traffic.

5.1 User classes

In this case study, the vehicle classes of cars and trucks are simulated. Furthermore, since traffic is guided via two routes, the user classes are further categorized into those
(a) Case 1: 500m loop and IVD data

(b) Case 2: 500m loop, IVD and trajectory data

(c) Case 3: 1000m loop, IVD and trajectory data

(d) Case 4: 1500m loop, IVD and trajectory data

**Figure 15:** Speed estimates from the Fastlane-based traffic state estimation in four different cases. Note that the red rectangle box in (b) indicates the region for the helicopter data collection.
Figure 16: Speed estimate comparison between case 1 and case 2 (based on case 2, in %).

(a) (Mixed-class) Speed observations from loop

(b) Speed estimates for car class (case 2)

(c) Speed estimates for truck class (case 2)

Figure 17: Class-specific speed estimates from the Fastlane-based traffic state estimation, compared with raw speed loop data.
that can be rerouted and those that cannot. By those means, only traffic that wants to
travel to Vaanplein can be rerouted at Spijkenisse via the alternative route (see Figure 2).
At the bifurcation point Spijkenisse, we split the classes into 18% that are reroutable
traffic, and the remaining part as non-reroutable traffic. In total, there are thus four user
classes simulated.

5.2 DTM measures

Three multi-class DTM measures are applied in the following simulation. For details
about their effects and implementation in Fastlane, refer to the papers cited below.

A multi-class route guidance (MCRG) measure (Schreiter et al., 2012) advises a route
to the travelers at a network bifurcation. Since it is multi-class, it controls each vehicle-
class individually. It controls the turnfraction, which can assume values between 0,
indicating to stay on the route, and 1, indicating to use the off-ramp. One multi-class
route guidance (MCRG) measure is set up at the bifurcation point between the main
route and the alternative route near Spijkenisse (see Figure 2). A second MCRG is
located at the alternative route after the Botlekbridge, where the alternative route is
connected to the main route. Those MCRG affect only the two reroutable user classes
outlined above. We assume full compliance of the drivers.

A multi-class ramp meter (MCRM) (Schreiter et al., 2011) controls the inflow into the
freeway at an on-ramp. For each class, vehicles queue up in a separate lane so that each
class can be granted access to the freeway individually. The MCRM is parameterized
by the desired composition that is flowing out, and the set point density that should
be reached downstream. The MCRM determines the total ramp flow according to the
ALINEA algorithm (Papageorgiou et al., 1991), and distributes it to the vehicle classes
according to the specified desired share. An MCRM is set up at the on-ramp connecting
the A4 to the A15. The signals for the desired share can vary between 0, indicating full
priority to trucks, and 1, indicating full priority to cars. The set point density can vary
between 0 and 200\( \frac{veh}{km} \), whereby the critical density of the link downstream of the merge
is 112\( \frac{veh}{km} \).

5.3 Experimental setup

The signals of the DTM measures are computed by an optimal control approach. Opti-
mal control uses Fastlane to predict the effects of the current traffic conditions and the
effects of the DTM measures to minimize a specified objective. In this experiment, the
objective is to minimize the total cost, which essentially is the total travel time weighted
by the value of time for each vehicle class. We assume value of time of 45\( \frac{C}{veh \cdot h} \) for
trucks and 15\( \frac{C}{veh \cdot h} \) for cars (Rijkswaterstaat, 2011).

The prediction horizon of the optimal controller is 1 h. The length of the control hori-
zon is 40 min with control interval lengths of 10 min, leading to four control intervals
in the prediction horizon. The optimization is performed by Matlab’s interior-point
optimization algorithm.
5.4 Results under regular conditions

This section presents the results of the experiments performed under regular traffic conditions. The results are illustrated in the figures by the data set of 30-03-2011 at 15:30. In the following, the results for the no control case, for the mixed-class controller and for the multi-class controller are shown. For comparison, Table 3 summarizes the performance of all examples.

No Control under regular conditions

Since the dataset is the same as in the example of the validation procedure in Section 3.2.1, the predicted traffic conditions were already shown in Figure 10. To review, the two bottlenecks at Km 44 and Km 56 are active so that congestion emerges and grows at these locations. The performance of the no control case is 47 900 €.

Mixed-class control under regular conditions

The results of the mixed-class controller are shown in Figure 18. The spatio-temporal speed plot shows that the congestion is significantly shorter.

The reason is that the route guidance measure at the first bottleneck guides a part of the reroutable traffic via the alternative route. As a result, less traffic has to pass the bottleneck at Spijkenisse so that the congestion is shorter there. Since the traffic stays on the alternative route (the route-guidance signal after the Botlekbridge is zero), less traffic is flowing into the congestion at Charlois. Of course, this congestion is only relocated to the alternative route. The ramp meter at the A4 is not activated.

Since the congestion at Spijkenisse is reduced, fewer vehicles are queued so that the performance of the mixed-class controller is better than in the no-control case. The performance of the mixed-class controller is 44 700 €, which is a relative improvement of 6.8 %.

Multi-class control under regular conditions

Figure 19 presents the results of the multi-class controller. The congestions at both bottlenecks are shorter than in the no control case, and even slightly shorter than in the mixed-class controller case.

Traffic is rerouted via the underlying network, again leading to less congestion on the main route compared to the no-control case. In contrast to the mixed-class controller, the multi-class controller splits the routing dependent on the vehicle class. Only cars are rerouted; furthermore, a small portion of the rerouted cars is sent back to the main route after the Boktlekbrug. By these measures, the more valuable trucks stay on the
main route, and the less valuable cars take the alternative route to reduce the demand at the bottleneck, which reduces the congestion at Km 44. The ramp meter at the A4 is again not activated.

Since the vehicles can be guided class-specifically, the valuable trucks stay on the main route, which improves the performance. The performance of the multi-class controller is 44 000 €, which is an improvement of 8.2% compared to the no-control case, and
1.5% compared to the mixed-class case.

5.5 Results under incidental conditions

This section presents the results of the experiments performed under incidental conditions. During the morning of 18-04-2011, an incident occurred at Km 54, which caused congestion.

No control under incidental conditions

The (predicted) traffic conditions of the no-control case are shown in Figure 20. The congestion caused by the incident grows heavily during the duration of the incident. The spillback partially blocks upstream off-ramps, which worsens the congestion even more. When the incident clears at 09:45, the congestion dissolves slowly and takes more than 20 min. The incident thus affects the traffic on the A15 long after it has been cleared. The performance of the no control case is 45 500 €.

![Figure 20: No-control case of the incident experiments, spatiotemporal speed.](image)

Single-class control under incidental conditions

Figure 21 shows the results for the mixed-class control case. The congestion caused by the incident is significantly shorter than in the no-control case. This reduces the spillback and the blocking of the off-ramps so that the congestion stays short. Consequently, the congestion dissolves within a few minutes after the incident is cleared.

All of the reroutable traffic is guided via the alternative route. Since the congestion spills back over the on-ramp of the A4, the ramp meter is activated and holds back traffic of the A4 by queuing cars and trucks on separate lanes. After the incident is cleared and the congestion is dissolved, the ramp meter releases the congestion of the A4.

The performance of the mixed-class control case is 40 000 €, which is an improvement of 11.9% compared to the no-control case.
Multi-class control under incidental conditions

The results of the multi-class controller are shown in Figure 22. The traffic state on the A15 seems very similar to the mixed-class controller. Here, too, traffic is rerouted via the underlying road and the ramp meter is activated due to the congested A15.

However, the multi-class controller improves the traffic conditions when congestion of the A15 is dissolved and the congestion of the A4 is released. The share of the MCRM is set to 0, which means that trucks are prioritized. As a consequence, first the valuable trucks are released from the queue, and thereafter the less valuable cars, as shown in Figure 22(c) by means of the number of queued vehicles.

The performance of the multi-class controller is 39,800 €, which is an improvement of 12.5% with respect to the no-control case and 0.7% with respect to the mixed-class controller.

5.6 Discussion

The experiments show that multi-class traffic control improves the traffic performance of the network. By implementing multi-class route guidance, the traffic stream of trucks and cars can be separated so that the less valuable classes can use an alternative route, and the valuable classes can stay on the main route. Through multi-class ramp metering, priority can be given to the valuable classes first. Currently, the traffic signals are optimized online for the two multi-class route-guidance controllers; the results can be viewed at the BOS-HbR Homepage (2012).

6 Conclusion

We have developed a new approach for dynamic traffic management. In our approach multiple vehicle classes are taken into account. In this paper, we distinguish between two vehicle classes, namely passenger cars and trucks, although the approach can be extended to include other classes as well. The approach is particularly well suited for
online application on road networks with high truck percentages, such as the Dutch A15 near the harbor of Rotterdam. Three applications for this freeway are developed.

At the core of our dynamic traffic management approach lies a multi-class kinematic wave traffic flow model, Fastlane. It includes dynamic pce values, which distinguishes it from other such models. The pce values are based on physical and behavioral characteristics of vehicles and drivers. Efficient simulation methods for freeway networks are developed.

The model was calibrated and validated for traffic flow predictions. Fastlane accurately predicts both regular conditions and irregular conditions such as with an incident. The methods are implemented and the online predictions can be viewed on the BOS-HbR Homepage (2012).

A multi-class traffic state estimation method was developed. The method deals with class specific input, but the traffic state estimation itself is also multi-class. The method combines an extended Kalman filter with the Fastlane model in its Lagrangian formulation. The Lagrangian formulation leads to more efficient computations than an Eulerian formulation, which makes it feasible to provide accurate online traffic state estimations.

Finally, we developed an approach for class-specific DTM in which trucks are rerouted differently than cars. By a multi-class optimal control approach, the total cost of traffic is minimized, regarding the different values of time for each class. It is shown that multi-class control provides advantages over mixed-class control. The current traffic

Figure 22: Results of multi-class control at an incident.
state prediction with control can also be viewed on the BOS-HbR Homepage (2012).

Further development of Fastlane includes a more advanced integration of all elements: for example, the prediction and control are currently based on the Eulerian coordinate system and apply a simpler traffic state estimation than presented here. Vice versa, the traffic state estimation method would benefit from the calibration and validation methods presented here. The multi-class node model in Lagrangian coordinates may be developed further for more efficient estimation, prediction and control on freeway networks and possibly urban networks.

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**References**


