Vehicle-class Specific Route-guidance of Freeway Traffic by Model-predictive Control

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Abstract

Few Active Traffic Management measures proposed in the past consider the distinction of different vehicle classes. Examples of vehicle-class specific measures are truck lanes and high-occupancy/toll (HOT) lanes. We propose that the distinction of different vehicle classes, with different flow characteristics and societal and economic function, can contribute to the effectiveness of traffic management measures.

In this paper, we develop a multi-class controller that reroutes the traffic class-specifically dependent on the vehicle class. The vehicle-class specific properties such as vehicle length and value of time are used in a model-predictive control approach to optimize the total time spent and the economic costs. Experiments in a simple network with synthetic data show that a multi-class controller outperforms a single-class controller. We further show that the value of time and the incident strength have an influence on which vehicle class is rerouted by the multi-class controller.

FIGURE 1 Multi-class Traffic – Dynamic passenger-car equivalents (pce) of vehicle classes

INTRODUCTION

In the past decades, congestion has severely increased. The consequences are long travel times and a low network performance. To reduce the negative effects of congestion, traffic control centers apply Active Traffic Management (ATM) measures on various levels. On a local level, the traffic is controlled by actuators like ramp meters, which restrict the inflow onto the freeway. Ramp metering algorithms like ALINEA (1) control the freeway traffic towards a specified set point, like a desired traffic density, to prevent traffic from breaking down and to keep it in free-flowing conditions near capacity. On a link-wide level of a few kilometers, variable speed limits (VSL) are used for dissolving stop-and-go waves (2) and as a means of mainstream metering (3). On a network-wide level, variable message signs advise a route to vehicles, be it the fastest route (4) or the system optimum (5, 6). For an overview of route-guidance approaches, refer to (7) and (8). These controllers influence the traffic in a single-class way, treating all traffic as one class, and therefore ignoring the class-specific effects.

However, vehicles classes differ in a number of ways, as is illustrated in the following by means of trucks and cars. Firstly, the maximum speed of passenger cars is generally much higher than that of trucks. Secondly, trucks emit much more exhaust and therefore have a higher impact on ecological goals. In terms of economics, the value of a truck is considered much higher than a car's; a factor of around three is common in the Netherlands (9). Another difference is the (effective) vehicle length, which affects the traffic flow. Let us analyze the effects of the latter in more detail.

Trucks are significantly longer than cars. As Figure 1 schematically shows, the differences in vehicle lengths lead to different vehicle spacings (rear-bumper to rear-bumper distance), dependent on the speed of the traffic. At a complete standstill of traffic (bottom of Figure 1), a truck occupies much more space than a car, since the vehicle's length contributes largely to the spacing. In free flow conditions (top of Figure 1), however, a truck and a car occupy nearly the same amount of space, since the net gap between the vehicles contributes largely to the spacing. This ratio of the spacing s_w of vehicle class w with respect to a reference class is referred to as passenger-car equivalent (pce)

$$\pi_w = \frac{s_w}{s_{car}}. \quad (1)$$

The pce value is thus dynamic and depends on the traffic state. Empirical observations have revealed that a truck's pce value varies between 1 and 5 depending on the traffic conditions (10). Let us now analyze the effects of this phenomenon on the optimal route guidance strategy.

Figure 2 shows a simple network with a main route and an alternative route. There are thus two possible routes traffic can use. A multi-class Variable Message Sign (VMS) is placed at the divergence of the two routes to guide the traffic class-specifically. The traffic consists of passenger cars and trucks. Due to the dynamics of the spacing (1), let the pce value of trucks in free flow be $\pi_{truck}(free) = 2^{pce/veh}$ and in congestion be $\pi_{truck}(cong) = 5^{pce/veh}$. Suppose an incident occurs on the main route, which causes the capacity to drop to $C_{main} = 500^{pce/h}$. Suppose further that there is a demand of $1000^{veh/h}$ of cars and $500^{veh/h}$

FIGURE 2 Example of class-specific rerouting

of trucks. This demand exceeds the capacity, which can be seen when comparing the demand in pce terms: $1000 \text{ veh/h} \cdot 1 \text{ pce/veh} + 500 \text{ veh/h} \cdot 2 \text{ pce/veh} = 2000 \text{ pce/h} > C_{\text{main}}$. The traffic can be rerouted via the alternative route, which has a capacity of $C_{\text{alt}} = 1000 \text{ pce/h}$. In the following, we will compare two routing strategies.

First, let all trucks be rerouted. Their demand matches exactly the capacity of the alternative route, since $500 \text{ veh/h} \cdot 2 \text{ pce/veh} = 1000 \text{ pce/h}$. On the main route, the demand of the cars exceeds the capacity, so that congestion emerges. Since both routes are fully loaded, the throughput of the network in pce/h is the joint capacity of 1500 pce/h . The throughput in veh/h is 1000 veh/h (namely 500 veh/h on the alternative and 500 veh/h on the main route).

Now, let us analyze the other control strategy and reroute all cars. Since the demand of the cars matches the capacity of the alternative route, all cars can be rerouted without creating additional congestion. On the main route, congestion emerges, since the remaining demand of the trucks exceeds its capacity. The throughput in pce/h is exactly the same as in the first control strategy, namely 1500 pce/h . However, the throughput in veh/h is now 1250 veh/h , since 1000 veh/h are flowing via the alternative route, and 250 veh/h on the main route. One effect of multi-class rerouting is therefore the option to maximize the *throughput* in veh/h .

However, a second effect comes into play: the *spillback* effect of the congestion. Cars have a pce value of 1 by definition, i.e. their relative spacing is not affected by the congestion. Trucks, however, occupy more relative space in congestion than in free flow, as illustrated earlier in this section. In the example, one truck in congestion equals five cars, compared to two cars in free flow. Routing trucks into congestion therefore makes the congestion grow faster. In the example, the congestion grows $\frac{\pi_{\text{truck}}(\text{cong})}{\pi_{\text{truck}}(\text{free})} = 2.5$ times faster if trucks are guided into the congestion, compared to when they are rerouted via the alternative route. Dependent on the network layout, the congestion growth can cause blocking back to upstream infrastructure such as off-ramps or junctions. If other flows that do not need to pass the bottleneck then get blocked, the network performance degrades.

There is thus a trade-off between a high throughput in the network and a low spillback of congestion. A multi-class controller therefore is useful to steer the network towards the desired performance, or to find a compromise between the two competing goals.

In this paper, we analyze predictive multi-class control of traffic. We thereby present an example focused on route-guidance control. The controller takes the properties of each vehicle class into account, in order to find the optimal route guidance signal. The actuator of such a route-guidance controller are in-car

FIGURE 3 The Model-predictive control (MPC) loop

navigation devices to be able to redirect a fraction of the flow.

To analyze the multi-class route-guidance controller thoroughly, an optimal and predictive control approach is chosen: by model-predictive control (MPC), the route guidance controller optimizes the signal over a short period of time.

MULTI-CLASS MODEL-PREDICTIVE CONTROL

A multi-class route-guidance controller has multiple control signals, namely one route guidance advice for each vehicle class. Multiple control signals can easily be optimized simultaneously by model-predictive control (MPC) (6).

MPC has been applied multiple times in urban traffic control and active traffic management on free-ways. In an urban context, MPC is used to optimize the cycle time to minimize the total time spent (11). For freeway networks, MPC is used to coordinate ramp meters (6) or to integrate them with route guidance (5, 12). Also, simulations with to control multi-class traffic flow have been performed, although with non-dynamic pce values (13).

The control loop is schematically shown in Figure 3. The real-world traffic process is observed so that its current state $y[j]$ is estimated, j indicating the time. The traffic is influenced by control inputs $u^*[j]$ that are controlled by the traffic operator, and disturbances $b[j]$ that are random. (Boldface variables refer to a vector over time of the respective variable.) Such a control input is, for example, the fraction of a vehicle class that is rerouted; disturbances are, for example, the traffic demands into the network.

The goal of the a model-predictive controller (MPC) is to find the control signal $u^*[j]$ that minimizes the objective function J :

$$u^*[j] = \arg \min_u J(y[j], u[j]) \quad (2)$$

subject to

$$y[j+1] = f(y[j], u[j], b[j], j), \quad (3)$$

This optimization procedure is repeated at every time step j . The objective function J describes the system performance in a single real value. Normally in traffic operations, the total time that vehicles spend in the network is used for this performance indication. The function f models the real-world process by means of a traffic flow model and predicts the system state over a finite time horizon. The first element $u^*[j]$ of the optimal control signal $\mathbf{u}^*[j]$ is applied to the actuators to influence the real-world process. To correct for the unknown disturbances and model inaccuracies, this optimization procedure is repeated in each time step j (receding time horizon).

EXPERIMENTAL SETUP

To compare the performance of multi-class control against single-class control, several experiments based on computer simulations are conducted. This section presents the experimental setup. The following section discusses the results.

Traffic Setup

A simple freeway network shown in Figure 4a is used. The main route has a large capacity of $C_{\text{main}} = 5610 \text{ pce/h}$, so that in normal conditions the traffic can flow through it without causing congestion. However, an incident occurs on the main route so that the capacity is reduced. This reduced capacity $C_{\text{inc}} = (1 - \omega) \cdot C_{\text{main}}$ depends on the incident strength ω . Dependent on C_{inc} , congestion can occur and spill back. Eventually, that spillback threatens to block the off-ramp that is located further upstream. Different incident strengths are simulated within a range of $\omega \in [0, 0.9]$. The incident occurs at the beginning of the simulation and lasts through the whole simulation period.

The network has one origin in the South and two destinations, one in the North at the end of the freeway and one in the East via the off-ramp. The demand pattern over the $T_{\text{sim}} = 3 \text{ h}$ of simulation is shown in Figure 4b.

There is an alternative route to guide the traffic around the incident. The alternative route is 5 km longer than the main route and has a capacity of $C_{\text{alt}} = 1870 \text{ pce/h}$. On both main and alternative route, vehicles can overtake each other as long as the traffic conditions are in free flow. To guide the vehicles, route-guidance is applied just upstream of the bifurcation to the alternative route where each vehicle is advised individually. For the sake of simplicity, we assume that every vehicle can be advised and that every driver complies to the given advice, i.e. the traffic follows the advised routes exactly.

The fundamental diagram for the alternative route is shown in Figure 4c. For different capacities, the fundamental diagram is simply scaled. In free flow conditions, cars drive faster than trucks. The fundamental diagram is therefore class-specific. Since in congestion the vehicles are forced to drive at the same speed, the congested branch is the same for all classes.

A further class-specific property is the value of time (VOT), denoted by ζ_w , which is used in one of the objective functions. Generally, the time of a truck is much more valuable than that of a car. In this paper, the VOT is based on the numbers from the Dutch road authority (9), with a car's VOT of $\zeta_{\text{car}} = 15 \text{ €/h}$ and a truck's VOT of $\zeta_{\text{truck}} = 45 \text{ €/h}$.

Controllers

Four controllers are simulated and compared:

1. Multi-class model-predictive control (MC MPC): The route guidance controller optimizes two class-specific control signals, one for cars and one for trucks.
2. Single-class model-predictive control (SC MPC): The route guidance controller optimizes one control signal, guiding all South-North traffic.
3. Single-class reactive control by measured travel times (SC TT): The control signal is based on measured travel times of the routes (e.g. as in (14)). The fastest route is advised to all vehicles.

FIGURE 4 Experimental Setup

4. No Control: No route advice is given. All traffic uses the main route.

Due to the network layout, only traffic that flows from South to North can be rerouted, i.e. the Eastbound traffic is not guided.

Model-predictive Controller Setup

This section describes the setup of the model-predictive controller (MPC). First, we briefly discuss the model. Then, we discuss the parameters of the controller. Finally, we present the objective function.

The traffic flow model Fastlane (15) is used both as the process model f and the real world process. Fastlane is a multi-class expansion of the first-order macroscopic model LWR (16, 17). For each vehicle class w , the conservation of vehicles holds:

$$\frac{\partial k_w}{\partial t} + \frac{\partial q_w}{\partial x} = 0, \quad (4)$$

for the class-specific vehicle density k_w and vehicle flow q_w over space x and time t . Similar to the Cell-Transmission Model (18), Fastlane is discretized into cells (length $\Delta x = 500$ m) and into time steps (length $\Delta t = 15$ s). The fundamental diagram (Figure 4c) is based on the total effective traffic density (in pce/km)

$$K_{\text{tot}} = \sum_w \pi_w(v) \cdot k_w, \quad (5)$$

which in turn is defined by the vehicular density k_w of each vehicle class w and the dynamic pce value $\pi_w(v)$.

As a distinction to other macroscopic, multi-class traffic flow models, Fastlane treats the pce value dynamically, dependent on the underlying traffic state (more precisely, the speed of each class). The pce function is modeled after a simple car-following model (19):

$$s = s^{\min} + v \cdot h^{\min}, \quad (6)$$

relating the spacing s to the spacing at standstill $s^{\min}$, the current speed v and the minimum time headway $h^{\min}$. Replacing the spacing of (1) with (6) yields the pce function used in Fastlane:

$$\pi_w = \frac{s_w^{\min} + v_w \cdot h_w^{\min}}{s_{\text{car}}^{\min} + v_{\text{car}} \cdot h_{\text{car}}^{\min}} \quad (7)$$

In the experiments, (7) is parameterized with $h_{\text{truck}}^{\min} = 1.2$ s, $h_{\text{car}}^{\min} = 1.2$ s, $s_{\text{truck}}^{\min} = 25$ m and $s_{\text{car}}^{\min} = 6$ m. The pce function of trucks is plotted in Figure 4d.

For the MPC parameters, calibration and testing have shown that a prediction horizon length of 60 min and a control interval of 10 min are sufficient; i.e. the controller optimizes the control signal every 10 min by predicting 60 min ahead. Longer horizons do not show a significant improvement of the network performance. Each control signal is bound by 0, indicating the main route, and 1, indicating the alternative route. The minimization (2) of the objective function is solved by a sequential-quadratic programming algorithm, as it is implemented in Matlab.

Multiple scenarios with different objective functions are simulated. First, the objective of the model-predictive controller is to optimize the total time spent (TTS). The total time spent is the sum of the travel times of all vehicles in the network. Since a cell-based traffic flow model is used, the TTS is derived from the vehicle densities $k_w^i[j]$ (with i as the cell index and j as the time index):

$$J^{\text{TTS}} = T_{\text{sim}} \cdot \sum_w \sum_i \sum_j k_w^i[j] \cdot \Delta x_i. \quad (8)$$

Second, for comparison, the economic costs are used as an objective function. The travel time of each vehicle is weighted by its value of time ζ_w :

$$J^{\text{cost}} = T_{\text{sim}} \cdot \sum_w \zeta_w \cdot \sum_i \sum_j k_w^i[j] \cdot \Delta x_i. \quad (9)$$

RESULTS AND DISCUSSION

This section presents the results and a discussion of the experiments, split into three topics. First, the performance of the four controllers is compared. Second, the influence of the value of time onto the multi-class MPC is presented. Third, the influence of the incident strength ω onto the multi-class MPC is analyzed.

Comparison of the Controllers

The four controllers are compared for both objective functions and for multiple different incident strengths. Example simulation results of all four controllers for the case of an incident strength of $\omega = 0.64$ and the optimization of the total time spent J^{TTS} (8) are shown in Figure 5. In these simulations, the incident strength is large enough to let congestion emerge at its location at Km 14.

The *multi-class MPC* reroutes some of the traffic via the alternative route, as the control signal in Figure 5b shows (rg_truck is the routing signal for trucks, rg_car the one for cars). Between 08.30 and 09.30 the traffic demand exceeds the joint capacity of the main road and the alternative road. Congestion therefore emerges at the bottleneck, as the spatio-temporal density plot in Figure 5a shows. However, the congestion stays at the bottleneck and does not affect other parts of the network. Both routes are used at their respective capacities. The performance of the Multi-class MPC is $J_{\text{MC MPC}}^{\text{TTS}} = 1950 \text{ veh}\cdot\text{h}$.

As can be seen in the control signals, the share of traffic being rerouted is not equally distributed between the vehicle classes. Significantly more cars were rerouted via the alternative route, whereas only a few truck were rerouted during peak traffic. Later in this paper, we will analyze the effect of the traffic state and the incident strength in more detail.

The *single-class MPC* performs slightly worse with $J_{\text{SC MPC}}^{\text{TTS}} = 2040 \text{ veh}\cdot\text{h}$. As with the MC MPC, the alternative route is used at capacity during the congestion. The congestion pattern (Figure 5c) is similar to the one of the MC MPC.

The difference in performance between the MC MPC and the SC MPC can therefore only be explained by the traffic composition of the two routes. Due to the nature of the SC MPC, it guides the traffic to the alternative route regardless of class (Figure 5d). The MC MPC, however, sends more cars than trucks via the alternative route. This is because during congestion, the travel time of the alternative route is shorter than that of the main road. Furthermore, since cars are shorter than trucks, more cars than trucks can flow through any given bottleneck. In other words, the throughput in veh/h is higher the more the traffic is composed of cars. Guiding cars via the faster, alternative route therefore leads to a higher total throughput. Figure 6 shows the difference of the cumulative vehicle count between the MC MCP and SC MPC scenario at the Northern exit over time. For example, at 09.00, 60 more vehicles more had arrived at the Northern exit in the MC MPC than in the SC MPC. The vehicles in the MC MPC therefore arrived faster at the destinations. A faster arrival means a lower total time spent and a better performance.

The *reactive single-class controller* can guide the traffic only in an all-or-nothing way. If the travel time on the alternative route is shorter, then all traffic is advised to use that route, as it happens at 08.30, as Figure 5f shows. Since the demand exceeds the alternative route's capacity, congestion emerges at Km 5 (Figure 5e). Since no traffic then uses the main road, the congestion at the incident location dissolves. This causes the travel time to decline, and the controller switches back to the main route at 09.00. This effect repeats a couple of times, leading to oscillations in the control signal.

The total time spent $J_{\text{SC TT}}^{\text{TTS}} = 3750 \text{ veh}\cdot\text{h}$ of the reactive controller is significantly higher than the predictive controllers'. One reason for this is that the reactive controller always acts delayed, not being able to anticipate the future traffic state. Another reason is the binary zero-one signal, which always leads to an underutilization of the infrastructure. Finally, since congestion emerges at the bifurcation to the alternative road, the Eastbound traffic is blocked as well, which drastically increases the TTS.

Although a zero-one signal is not very realistic, this scenario shows the disadvantage of the oscillations of the control signal. Furthermore, the controller only reacts on the travel time and does not directly optimize the objective of total time spent. It therefore cannot take the Eastbound traffic into account and is

(a) Multi-class MPC, main route

(b) Multi-class MPC, Control signal

(c) Single-class MPC, main route

(d) Single-class MPC, Control signal

(e) Single-class reactive TT, main route

(f) Single-class reactive TT, Control signal

(g) No Control, main route

FIGURE 5 Simulation results of the four controllers (incident strength $\omega = 0.64$, objective function total time spent J^{TTS})

FIGURE 6 Difference of Total Vehicle Count at Northern exit between MC MPC and SC MCP

insensitive to its amount.

For comparison, the base case of *no control* is shown in Figure 5g. Since the traffic is not guided at all, the alternative route is not used. The traffic therefore queues up at the bottleneck and severe congestion emerges. The performance with $J_{NoCtrl}^{TTS} = 6260 \text{ veh}\cdot\text{h}$ is therefore inferior to the other scenarios.

In summary, the multi-class MPC performs slightly better than the single-class MPC. Both MPC controllers outperform the reactive controller. (Note that the comparison with the reactive control is somewhat simplified, since the reactive controller is relatively simple, such as rerouting in all all-or-nothing fashion, or reacting with with relatively large control intervals.) The no-control case is the worst.

This trend is also visible for other incident strengths and for the objective of minimizing the economic costs, especially for the cases in which congestion cannot be prevented ($\omega \geq 0.6$). Figure 7 shows the performance of the controller over different incident strengths ω for the total time spent J^{TTS} (8) and for the economic costs J^{cost} (9). (For readability, the performance results of the non-MPC controllers have been omitted for heavy incidents, which led to a very high objective values.)

The influence of the Value of Time

This section analyzes the results of the multi-class MPC for the two objective functions, aiming at the minimization of the total time spent J^{TTS} (8), and the minimization of the economic costs J^{cost} (9). Note that the difference between these two is only the class-specific value of time ζ_w . In the following, four example simulation runs are presented and compared. Figure 8 shows the control trajectories of the MC MPC for both objective functions and for different incident strengths.

Let us first analyze the control signal during a *light incident* ($\omega = 0.4$). Congestion is prevented by rerouting some of the traffic via the alternative route. For the objective of total time spent (meaning that a truck essentially has the same value of time as a car), trucks are rerouted via the slower alternative, as shown in Figure 8a. Therefore, there are many short vehicles (cars) on the main route, which leads to a high throughput on the main route, and thus to a low TTS.

On the other hand, for the objective of economic cost (meaning that a truck is essentially three times as valuable as a car), the prioritization by the controller changes, as Figure 8b shows. In this case, it is advantageous to reroute some of the cars instead. Then, the trucks experience a short travel time. The loss of throughput (in $\text{veh}\cdot\text{h}$) on the main route is compensated for by the higher value of time of the trucks, which thus leads to low costs.

Let us now analyze the control signal during a *heavy incident* ($\omega = 0.7$). In this case, congestion is severe and leads to long travel times on the main road. In the case of the objective of total time spent, cars are guided via the alternative route. Since the alternative route is faster, throughput is maximized there by using it for short vehicles, which leads to a low TTS.

On the other hand, for the objective of economic costs, the valuable trucks are rerouted instead. Similarly to the case of the light incident, to minimize the costs it is advantageous to enable a short travel

(a) Objective minimize total time spent J^{TTS} (b) Objective minimize economic costs J^{cost} **FIGURE 7 Performance of the four controller for varying incident strengths**

time for the valuable vehicles.

In summary, the multi-class controller uses the ability of realizing different prioritizations depending on the value of time. The more valuable a vehicle is, the faster it should travel through the network. The control signals therefore can change drastically if the value of time is changed.

The influence of the Incident Strength

This sections analyzes the influence of the incident strength onto the control signals of the multi-class MPC. The objective function used is the total time spent with a slight adjustment: the Eastbound traffic is considered very important, and delays thereof thus have to be avoided at (almost) all costs; therefore, a penalty term is added to the objective function. In the following, we will discuss the rerouting of the vehicle classes by the controllers depending on the incident strength. We will analyze six example simulation runs, differing in the incident strength. We start with the lowest one.

In the case of *no incident* ($\omega = 0$), the capacity of the main route is sufficiently large so that the traffic can flow freely without causing congestion (Figure 9a) and (almost) no rerouting is necessary (Figure 9b).

In the case of a *tiny incident* ($\omega = 0.3$), some of the vehicles are rerouted (Figure 9d) via the alternative route to prevent congestion. Figure 9c presents the travel times for both vehicle classes on both routes. As can be seen, cars traverse the alternative route in 7.5 min (blue dashed line), whereas trucks need 10 min (red dashed line). Cars are thus much faster than trucks on that route. Rerouting cars via the fast alternative route therefore leads to the optimal TTS.

In the case of a *light incident* ($\omega = 0.4$), more vehicles have to be rerouted to prevent congestion.

FIGURE 8 Control Signals of the Multi-class MPC for different values of time and different incident strengths

Since many vehicles now have to use the alternative route, the density is nearly critical, so that all vehicles drive at nearly the same speed. As Figure 9e shows, at 08.30, the travel time for cars is 9 min, and for trucks it is 10 min. The travel times are thus almost equal on that route. Therefore, it is optimal to keep the small vehicles on the fastest route in order to maximize the throughput (Figure 9f). The fastest route is the main route, where the travel is 5 min for both classes.

In the case of a *medium incident* ($\omega = 0.66$), the demand exceeds the joint capacity of both routes, and congestion emerges at the incident location (Figure 10a). Since the alternative route is now faster than the main route, more cars than trucks are rerouted via the alternative route (Figure 10b).

The more the congestion increases, the more cars are expected to be rerouted via the alternative route. However, another effect becomes decisive in the case of a *medium-heavy incident* ($\omega = 0.68$). The congestion threatens to spill back over the off-ramp at Km 10 (Figure 10c), and thereby blocking the Eastbound traffic. The controller manages to prevent such a spillback by rerouting more trucks via the alternative route (Figure 10d) and instead placing short cars into the congestion. The reason for this is the dynamic pce value of the trucks: as illustrated earlier, in congestion, a truck occupies significantly more space than a car; in free-flow (as is present on the alternative route), a truck occupies only slightly more space than a car. Consequently, the throughput of the alternative route decreases. In other words, the prevention of spillback to the off-ramp outweighs the reduction of throughput of the alternative route.

In the case of a *heavy incident* ($\omega = 0.70$), congestion reaches back to the on-ramp and spillback can no longer be prevented after 09.00 (Figure 10e), so that all vehicles including the Eastbound traffic experience congestion. Since the Eastbound traffic is now delayed, the total time spent increases severely. The throughput is maximized by rerouting the small cars via the alternative route (Figure 10f). Given the constraints by this heavy incident, the solution is optimal, when the controller puts the congestion at the bifurcation point. It controls the traffic in such a way that the downstream congestion does not block the

FIGURE 9 Results of Multi-class MPC for different incident strengths

off-ramp.

In summary, the rerouting of the vehicle classes by the controller depends on the severity of the incident. The rerouting thereby is not monotonically related to the incident strength, but varies for different scenarios. Table 1 summarizes the results of the rerouting of the multi-class MPC dependent on the incident strength.

CONCLUSION

In this paper, we introduced vehicle-class specific control for Active Traffic Management. The effects of different vehicles classes on the network performance were analyzed. Specifically, we looked at the class-specific vehicle spacing and the class-specific value of time. The vehicle spacing affects the traffic flow both in terms of throughput and of congestion spillback. Cars, which are relatively short, enable a higher throughput than trucks and show a less severe congestion spillback than trucks. On the other hand, trucks are considered economically more valuable than cars.

The multi-class controller we developed takes these phenomena into account by predicting their

FIGURE 10 Results of Multi-class MPC for different incident strengths (cont.)

occurrence by means of model-predictive control (MPC). By optimizing the control signal for the expected near-future traffic state, the controller is able to steer the traffic system towards a system optimum.

Findings

In experiments, the multi-class model-predictive controller outperforms the single-class controller. Especially during congestion, the multi-class controller is able to distribute the vehicle classes over different routes, in order to enable a short travel time for one of the classes, or to reduce spillback effects. Furthermore, both the multi-class and the single-class MPC were compared to a simple reactive controller. The predictive controllers outperform the reactive one.

As objective functions, we compared the total time spent, which is the sum of all vehicles' travel times, and the economic cost, which weights the travel times by the class-specific value of time. These two functions differ essentially only in the value of time. For the economic cost, we considered a truck three times as valuable as a car. This slight difference in the objective functions led to huge differences in the

Incident strength	Class rerouted	Reason
no incident	—	no delay
tiny incident	cars	on alternative route, much shorter TT for cars compared to trucks
light	trucks	same TT on alternative route, while higher throughput on faster main route
medium	cars	alternative route faster than main route
medium-heavy	trucks	prevent spillback
heavy	cars	cannot prevent spillback, alternative route faster than main route

TABLE 1 Rerouting of the vehicle class by the multi-class MPC dependent on the incident strength

controller signals of the multi-class MPC. In the case of the total time spent, the cars are assigned the fastest route, in general. The reason is the maximization of throughput. In the case of the economic costs, trucks are assigned the fastest route. The reason is the low travel time for valuable vehicles. Due to the modularity of MPC, other objective functions can be applied in a straight-forward manner. For example, the minimization of emissions, including a weighting for vehicle classes and road type can be implemented, in order to reduce the impact on densely populated areas.

A further determining factor on the multi-class MPC signal is the severity of the incident. Counter-intuitively, the type of the rerouted vehicle class does not depend monotonically on the incident strength. Instead, the vehicle-class rerouted switches multiple times with increasing incident strength. In light cases of incidents, the travel times of the available routes are the dominant factor. If only a few vehicles have to be rerouted, then the rerouting of cars is beneficial, since they can travel much faster than trucks. If many vehicles have to be rerouted, then the travel time of the alternative route deteriorates. In that case, cars should stay on the main route, and trucks should use the alternative route. By this measure, the throughput is maximized and the total time is minimized.

In severe cases of incidents, the prevention of spillback to upstream infrastructure is the dominant factor. The latter one causes long vehicles such as trucks to be rerouted and kept out of the congestion. Although this measure decreases the joint throughput of the available routes, the prevention of spillback leads to the minimization of the total time spent. Finally, in very severe cases of incidents when spillback cannot be prevented, then cars should be rerouted again.

Further Research

For practical applications, multi-class route guidance can therefore be beneficial if the vehicles can be addressed class-specifically. Especially with the combination of model-predictive control, Active Traffic Management during exceptional conditions such as incidents or evacuations can be improved. To achieve these goals, the current traffic state has to be estimated, the intended destinations of the vehicles have to be known, and the traffic has to be controllable on an individual basis. With a wide implementation of in-car navigation devices, large penetration rates of smart phones or similar techniques, we believe that such a class-specific control approach is to a large extent both possible and beneficial in the future.

To move towards practical applicability of multi-class control, the performance improvement has to be researched under more realistic setups such as partially-known traffic states, partial compliance or model inaccuracies. Furthermore, for a better comparison between multi-class predictive controllers and current state of practice, realistic fine-tuned reactive controllers can be added to the benchmark.

In further research, we want to analyze the effect of the network layout on the performance difference between the multi-class controller and the single-class controller. For instance, if the alternative

route provided had some buffer space, then the separation of the vehicle classes would be easier. To provide spillback, for example, more trucks could be rerouted and buffered on the alternative route, thereby preventing congestion on the main route. In such a case, the performance improvement by applying a multi-class controller is expected to be larger.

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