Delft University of Technology

Delft Center for Systems and Control

Technical report 09-027

Model-based traffic control for balanced reduction of fuel consumption, emissions, and travel time*

S.K. Zegeye, B. De Schutter, H. Hellendoorn, and E. Breunesse

If you want to cite this report, please use the following reference instead:
S.K. Zegeye, B. De Schutter, H. Hellendoorn, and E. Breunesse, "Model-based traffic control for balanced reduction of fuel consumption, emissions, and travel time," *Proceedings of the 12th IFAC Symposium on Transportation Systems*, Redondo Beach, California, pp. 149–154, Sept. 2009. doi:10.3182/20090902-3-US-2007.0018

Delft Center for Systems and Control
Delft University of Technology
Mekelweg 2, 2628 CD Delft
The Netherlands
phone: +31-15-278.24.73 (secretary)
URL: https://www.dcsc.tudelft.nl

Model-based traffic control for balanced reduction of fuel consumption, emissions, and travel time

Solomon K. Zegeye * **Bart De Schutter** * **Hans Hellendoorn** *
Ewald Breunesse **

* *Delft University of Technology, 2628 CD Delft, The Netherlands (Tel.: +31-15-27-86524; e-mail: s.k.zegeye@tudelft.nl, b@deschutter.info, j.hellendoorn@tudelft.nl).*
** *Shell Nederland B. V., Carel van Bylandtlaan 30, 2596 HR The Hague, The Netherlands, (e-mail: ewald.breunesse@shell.com)*

Abstract: In this paper we integrate the macroscopic traffic flow model METANET with the microscopic dynamic emission and fuel consumption model VT-Micro. We use the integrated models in the model predictive control (MPC) framework to reduce exhaust emissions, fuel consumption, and travel time using dynamic speed limit control. With simulation experiments we demonstrate the countereffects and conflicting nature of the different traffic control objectives. Our simulation results indicate that a model-based traffic control approach, particularly MPC, can be used to obtain a balanced trade-off between the conflicting traffic control objectives.

Keywords: Dynamic traffic management, model-based control, traffic control, emissions, fuel consumption

1. INTRODUCTION

There are several possible solutions to address the problems related to emissions, fuel consumption, and travel time of road traffic. Large-scale substitution of fossil oil by alternative fuels, enhancing vehicle technology, extending existing infrastructures, and implementation of intelligent transportation systems are possible approaches to tackle the multifaceted traffic challenges. However, due to several reasons the last solution is the most sound approach to address the problems (van den Berg et al., 2003; Kotsialos et al., 2002). In intelligent transportation systems, different traffic flow control measures (such as traffic signal, ramp metering, speed control, route guidance, etc.) can be used to minimize the impacts of traffic jams (such as additional emissions and fuel consumption and longer travel times) and to optimize the performance of the traffic network.

In traditional traffic-assignment problems, only a single objective — travel time or travel cost — is considered (Benedek and Rilett, 1998; Tzeng and Chen, 1993). However, reduction of travel time or improvement in the flow of traffic does not always guarantee reduction of the traffic-related nuisances such as air pollution, noise, and fuel consumption (Ahn and Rakha, 2008; Benedek and Rilett, 1998; Zegeye et al., 2008). In (Tzeng and Chen, 1993) for example, a multi-objective traffic assignment that incorporates emissions, travel time, and travel distance is investigated. There, the authors considered different weightings of the constituent objectives and suggested that the three performance criteria are conflicting to each other. However, their study is based on a static traffic demand and they used traffic assignments to solve the problem. Furthermore, the work of Benedek and Rilett (1998) provides more insight into the effects of taking travel time as a performance criterion on emissions and the other way around. i.e. they consider one objective at a time for a traffic assignment to address the problem of either environmental pollution or travel time and studied the countereffect. Moreover, they use macroscopic traffic flow and emission models. However, since macroscopic emission models do not take acceleration into account, the models do not in general capture the full emissions of traffic flow (Ahn et al., 1999; Ahn and Rakha, 2008; Benedek and Rilett, 1998).

In this paper, we first integrate the macroscopic traffic flow model METANET (Messmer and Papageorgiou, 1990) with the microscopic emission model VT-Micro (Ahn et al., 1999). In this way we incorporate the dynamics in the speed of the traffic flow into the emission model and we get better estimates and predictions of the emissions of the traffic flow. Moreover, due to the conflicting nature of emissions, fuel consumption, and travel time, and due to the dynamic nature of the traffic demand, we propose a model-based dynamic traffic control approach. In this approach we consider a multi-criterion objective function that comprises the environmental factors and travel cost (particularly emissions, fuel consumption, and travel time) with dynamic speed limit as control measures. With the help of a simulation study we show that the approach can be used to reduce both emissions and fuel consumption while still improving the traffic flow.

The paper is organized as follows. First we present the traffic flow models and the fuel consumption and emission models used in the study in Section 2. Next we propose a model-based control approach for the system in Section 3. Section 4 considers the optimization problem and in Section 5 we discuss and present our case study and its results to demonstrate the proposed approach. Finally we provide our conclusions in Section 6.

[1] Bart De Schutter is also with the Marine & Transport Technology department of Delft University of Technology.

2. MODELS

2.1 Traffic flow models

We consider METANET (Messmer and Papageorgiou, 1990) to simulate the traffic flow of a freeway. METANET is a macroscopic traffic model that describes the average behavior of vehicles in a traffic network. In this modeling technique, a link (a homogeneous freeway) is divided into a number of segments where the traffic behavior in each segment is described by a set of dynamic equations. These dynamic equations describe the density, flow, and average speed of the traffic flow in each segment.

The equations used to calculate the traffic variables for every segment i of a link are given by [2] :

$$q_i(k) = \lambda \rho_i(k) v_i(k) \tag{1}$$

$$\rho_i(k+1) = \rho_i(k) + \frac{T}{L\lambda}\left[q_{i-1}(k) - q_i(k)\right] \tag{2}$$

$$\begin{aligned} v_i(k+1) = v_i(k) &+ \frac{T}{\tau}\left[V[\rho_i(k)] - v_i(k)\right] \\ &+ \frac{T v_i(k)\left[v_{i-1}(k) - v_i(k)\right]}{L} \\ &- \frac{T\eta\left[\rho_{i+1}(k) - \rho_i(k)\right]}{\tau L\left(\rho_i(k) + \kappa\right)} \end{aligned} \tag{3}$$

$$V[\rho_i(k)] = v_{\text{free}} \exp\left[-\frac{1}{b}\left(\frac{\rho_i(k)}{\rho_{\text{cr}}}\right)^b\right] \tag{4}$$

where q_i, ρ_i, and v_i, denote the flow, density, and space-mean speed of segment i of the link, T denotes the simulation time, L denotes the length of the segments of the link, and λ denotes the number of lanes of the link. Furthermore, v_{free} the free-flow speed, ρ_{cr} the critical density, τ a time constant, η the anticipation constant, b the parameter [3] of the fundamental diagram, and κ is the model parameter. METANET can also include lane drops, merging lanes, on-ramps, and so on (Hegyi, 2004; Kotsialos et al., 2002; Messmer and Papageorgiou, 1990).

Shock waves are fundamental characteristic of a traffic system. In METANET this phenomenon can be modeled by considering two different values of the anticipation constant η (Hegyi, 2004).

The dynamic equations described above describe traffic flow under uncontrolled speed limits. However, in our study we impose dynamic speed limit control on some of the segments of the link. Therefore, on the controlled segments of the link the desired speed $V[\rho(\cdot)]$ in (4) is replaced by (Hegyi, 2004):

$$V[\rho_i(k)] = \min\left\{ v_{\text{free}} \exp\left[-\frac{1}{b}\left(\frac{\rho_i(k)}{\rho_{\text{cr}}}\right)^b\right],\ (1+\alpha) v_{\text{lim},i}(k) \right\} \tag{5}$$

where $v_{\text{lim},i}(k)$ is the speed limit control input for segment i at time step k, and $(1+\alpha)$ is the compliance factor.

Since the demand at the origin of a link (or freeway) can exceed the capacity or the number of vehicles that can enter the freeway, a queue may develop. The dynamics of the queue w_{o} is modeled as:

$$w_{\text{o}}(k+1) = w_{\text{o}}(k) + T\left(d_{\text{o}}(k) - q_{\text{o}}(k)\right) \tag{6}$$

where d_{o} is the demand at the origin and q_{o} is the outflow of the origin. The outflow q_{o} is dependent on the number of vehicles that want to enter to the origin of the freeway, the capacity of the origin, and the number of vehicle that can enter the origin. This is expressed as:

$$q_{\text{o}}(k) = \min\left[d_{\text{o}}(k) + \frac{w_{\text{o}}(k)}{T}, C_{\text{o}}, C_{\text{o}}\left(\frac{\rho_{\text{jam}} - \rho_1(k)}{\rho_{\text{jam}} - \rho_{\text{cr}}}\right)\right] \tag{7}$$

with C_{o} is the capacity flow of the origin and ρ_{jam} is the maximum density of the link. Moreover, in the METANET model the speed of the origin of the link is set equal to the speed of the first segment of the link. Mathematically,

$$v_{\text{o}} = \begin{cases} \min\{v_{\text{lim},1}(k), v_1(k)\} & \text{if segment 1} \\ & \text{is controlled} \\ v_1(k) & \text{otherwise} \end{cases}. \tag{8}$$

The downstream boundary condition is mostly assumed to be congestion-free. But if a downstream density ρ_{d} is defined, the virtual downstream density is taken to be:

$$\rho_{N+1}(k) = \min\{\rho_{\text{d}}(k),\ \rho_N(k)\} \tag{9}$$

where N is the number of segments in the link.

2.2 Emission and fuel consumption models

Traffic emission and fuel consumption models calculate the emissions produced and fuel consumed by vehicles based on the operating conditions of the vehicles. Both emissions and fuel consumption of a vehicle are influenced by the vehicle technology, vehicle status (such as age, maintenance, etc.), vehicle operating conditions, the characteristics of the infrastructure, and external environment conditions. For a given vehicle technology and status of a vehicle, emission and fuel consumption models can be calibrated for every vehicle, or for homogeneous vehicle categories. The main inputs to the models are the operating conditions of the vehicle (such as speed, acceleration, engine load) (Heywood, 1988).

In general, emission and fuel consumption models are calibrated based on the operating conditions of the vehicle in a traffic flow. These models can be either *average-speed-based* or *dynamic*. Average-speed-based emission and fuel consumption models estimate or predict traffic emission and fuel consumption based on the trip-based average speed of traffic flow (Ntziachristos and Samaras, 2000). These models can also be used with local speeds to take some of the variation of the speeds into account (Boulter et al., 2002). On the contrary, dynamic (or also called microscopic) emission and fuel consumption models use second-by-second speed and acceleration of individual vehicles to estimate or predict emission and fuel consumption. Such model provide better accuracy than average-speed-based models.

VT-micro (Ahn et al., 1999) is a microscopic dynamic emission and fuel consumption model that yields emissions and fuel consumption of one individual vehicle using second-by-second speed and acceleration. The model has the form:

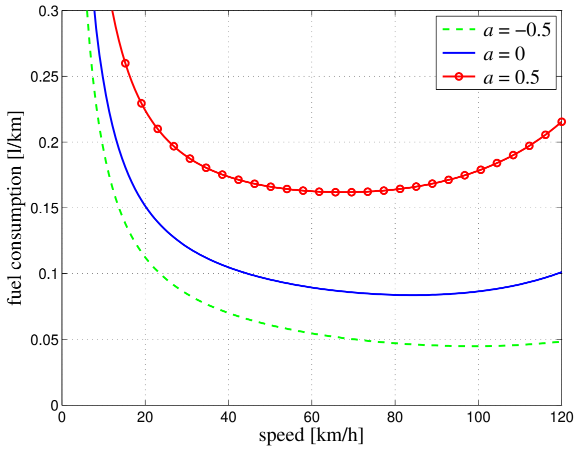
$$J_x(k) = e^{\left(\tilde{v}^T(k) P_x \tilde{a}(k)\right)} \tag{10}$$

where J_x is the estimate or prediction of variable $x \in$ {emission gases, fuel consumption}, $v(k)$ and $a(k)$ are respectively the speed and acceleration with the operator $\tilde{}$ defined for $z \in \mathbb{R}$

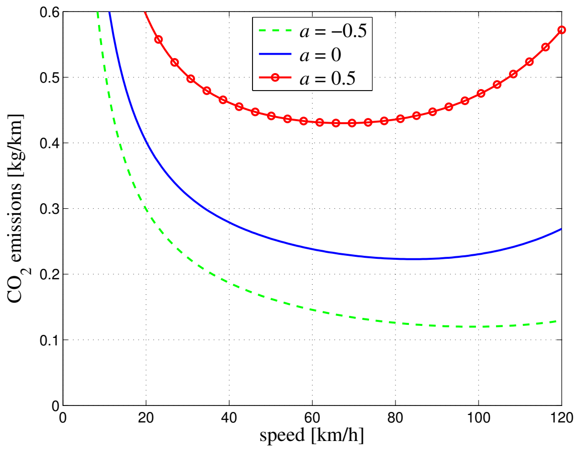
---

[2] In general all variables have also a subscript for their link index m, but since we consider only one link in our case study we drop the index m for simplicity of notation.

[3] In the original METANET model the parameter b is denoted by a. But to avoid confusion with the acceleration (which will be indicated with a in this paper) we chose to use b.



(a) Fuel consumption



(b) CO_2 emissions for diesel fuel

Fig. 1. CO emission and fuel consumption curves of vehicles as a function of the speed for accelerations $a \in \{-0.5,\ 0,\ 0.5\}$ m/s.

as $\tilde{z} = [1\ \ z\ \ z^2\ \ z^3]^T$, and P_x the model parameter matrix for the variable x. The value of P_x can be found in (Ahn et al., 1999).

Fig.1(a) depicts the fuel consumption versus the vehicle speed for three acceleration values generated from the VT-micro model. In our study we chose this model because it is simple and it takes the acceleration of the vehicle into account.

2.3 Integrating METANET with VT-micro

The VT-micro model is a microscopic traffic emission and fuel consumption model while METANET is a macroscopic traffic flow model. Thus, these two different models have to be integrated in such a way that the VT-micro model can get speed and acceleration inputs of the traffic flow from the METANET model at every simulation time step. The speed of the traffic flow can be easily obtained from (3). However, the computation of the acceleration is not as straightforward. In the sequel we show how to obtain the acceleration from the METANET model.

Consider a segment of a link as in Fig. 2. The figure shows the traffic flow at time step k and $k+1$. At the time k the number of vehicles in segment i is equal to $L\lambda\rho_i(k)$ and the number of vehicles going from segment i to segment $i+1$ in the time step k to $k+1$ is $Tq_i(k)$. Therefore, the number of vehicles that

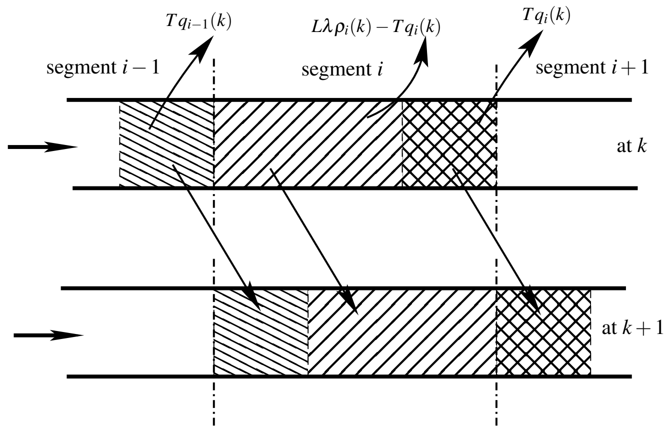


Fig. 2. Illustration of traffic flow in METANET

stayed in segment i in the period from time step k to time step $k+1$, i.e. $[kT,\ (k+1)T]$ is equal to $L\lambda\rho_i(k) - Tq_i(k)$. From time step k to $k+1$ the acceleration is not only due to the change in speed of the vehicles within the segment i, but also there is an acceleration for the vehicles flowing from segment $i-1$ to segment i. Hence we have the following accelerations:

$$a_{\Delta i}(k) = \frac{v_i(k+1) - v_{i-1}(k)}{T} \tag{11}$$

$$a_i(k) = \frac{v_i(k+1) - v_i(k)}{T} \tag{12}$$

where $a_{\Delta i}$ denotes the acceleration of the vehicles flowing from segment $i-1$ at k into segment i at $k+1$ and a_i denotes acceleration of the vehicles that are staying in segment i during the period $[kT,\ (k+1)T]$.

Therefore, at time step $k+1$, we provide the VT-micro model with two accelerations and two speeds along with their corresponding number of vehicles, i.e., we have the pair $(v_{i-1}(k),\ a_{\Delta i}(k))$ with $Tq_{i-1}(k)$ being the number of vehicles and the pair $(v_i(k),\ a_i(k))$ with $L\lambda\rho_i(k) - Tq_i(k)$ as the number of vehicles.

With the input pairs discussed above, the VT-micro model of (10) model gets changed to:

$$\begin{aligned} \bar{J}_{x,i}(k) = (L\lambda\rho_i(k) - Tq_i(k))\, e^{\left(\tilde{v}_i(k) P_x \tilde{a}_i^T(k)\right)} + \\ Tq_{i-1}(k) e^{\left(\tilde{v}_{i-1}(k) P_x \tilde{a}_{\Delta i}^T(k)\right)} \end{aligned} \tag{13}$$

where the $\tilde{\cdot}$ operator is defined as in (10). We call this model the "VT-macro" emission and fuel consumption model. This can be interpreted as the total emission and fuel consumption of a segment from time step k to time step $k+1$.

The VT-micro emission model of Ahn et al. (1999) does not yield estimates of CO_2 emissions. But, since there is almost an affine relationship between fuel consumption and CO_2 emissions (Oliver-Hoyo and Pinto, 2008), we can compute the CO_2 emissions as:

$$\bar{J}_{CO_2,i}(k) = \delta_1 + \delta_2 \bar{J}_{\text{fuel},i}(k) \tag{14}$$

where δ_1 and δ_2 are the model parameters. The values $\delta_1 = 1.17$ and $\delta_2 = 26.5$ can be found in (Oliver-Hoyo and Pinto, 2008) for a diesel-fuel car when the fuel input $\bar{J}_{\text{fuel},i}(k)$ in (14) is in l/100 km and the emissions $\bar{J}_{CO_2,i}(k)$ are in g/km. But, since the fuel output of the VT-macro model in (13) is given in l/s and since we want the CO_2 emissions also in kg/s just as the other emissions in the VT-macro model, we get

$$\bar{J}_{CO_2,i}(k) = 1.17 \cdot 10^{-6} v_i(k) + 2.65 \bar{J}_{\text{fuel},i}(k) \ .$$

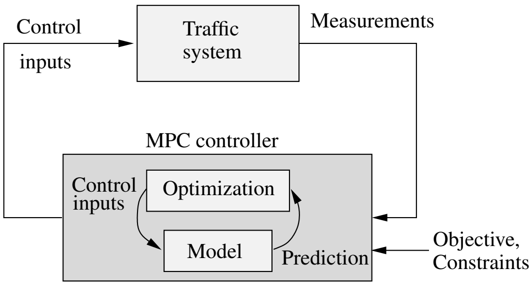


Fig. 3. Conceptual representation of model predictive control.

The CO_2 emission curves for a diesel-fuel vehicle are plotted in Fig. 1(b). The figure shows the variation of the emission values for three different accelerations.

3. MPC FOR TRAFFIC FLOW

Model predictive control (MPC) (Maciejowski, 2002; Camacho and Bordons, 1995) is a dynamic control approach that uses optimization of the control inputs based on prediction and a moving horizon approach. The basic concept can be explained with the help of Fig. 3 as follows. The MPC controller incorporates models of the traffic flow, emission, and fuel consumption. At control time step k_c (corresponding to the time instant $t = k_c \cdot T_c$ where T_c is the control sampling time), the controller collects measurements (such as density, flow, emission, etc.) of the traffic system through sensors. Based on the obtained or estimated current states and using the models, the controller predicts the future evolution of the traffic states up to time step $k_c + N_p$, where N_p denotes the prediction horizon. Using on-line optimization techniques the controller generates a sequence of traffic control inputs that minimize the defined objective function into the future. But, only the first control input is applied to the traffic system. At the next control time step $k_c + 1$, the controller again collects the newly changed traffic states, and it does the same operations as before. In this way, the controller continuously updates the control inputs based on the continuously changing demand and traffic dynamics of the system.

MPC for traffic control (or similar approach) has already been applied in literature (Bellemans et al., 2006; Gartner, 1984; Hegyi et al., 2005; Kotsialos et al., 2002). Its main advantages are that it can handle constraints (such as maximum emission levels), it can be applied to nonlinear models (e.g. nonlinear traffic models), and it can also be used to address multi-criteria optimization (such as emissions, fuel consumptions, and travel time). The main disadvantage of MPC emanates from the computation time required for on-line optimizations. However, there are different methods to reduce the computational time. One possible solution is to define a control horizon N_c, where after $k_c + N_c - 1$, the control input is made constant. Another solution is to reduce N_p and increase T_c, or to use blocking Maciejowski (2002).

Since one of the goals in increasing the efficiency of a vehicle engine or the purity of fuel is to maximize the conversion of the fuel to CO_2, it may have adverse effect on the overall global warming. Thus, as a performance measure we consider an objective function J_{obj} that incorporates CO_2 emissions $\bar{J}_{CO_2}$, fuel consumption $\bar{J}_{fuel}$, and total time spent TTS. It is described as:

$$\begin{aligned} J_{\mathrm{obj}}(k_c) = {} & \frac{\theta_1}{\bar{J}_{\mathrm{CO_2,nom}}} \sum_{k=Mk_c}^{M(k_c+N_p)-1} \sum_{i=1}^{N} \bar{J}_{\mathrm{CO_2},i}(k) \\ & + \frac{\theta_2}{\bar{J}_{\mathrm{fuel,nom}}} \sum_{k=Mk_c}^{M(k_c+N_p)-1} \sum_{i=1}^{N} \bar{J}_{\mathrm{fuel},i}(k) \\ & + \theta_3 \frac{\mathrm{TTS}(k_c)}{\mathrm{TTS_{nom}}} \end{aligned} \tag{15}$$

where

$$\mathrm{TTS}(k_c) = \sum_{k=Mk_c}^{M(k_c+N_p)-1} \left(\sum_{i=1}^{N} L\lambda\rho_i(k) + w_o(k) \right) T \tag{16}$$

is the total time spent in the freeway and in the origin queue, θ_i for $i \in \{1,2,3\}$ are the weighting factors of the constituent elements of the objective function, N is the number of segments of a link, and $\bar{J}_{\mathrm{CO_2,nom}}$, $\bar{J}_{\mathrm{fuel,nom}}$, and $\mathrm{TTS_{nom}}$ are the "nominal" values of respectively the CO_2 emissions, fuel consumption, and total time spent. For example in our case study (see Section 5) the nominal values correspond to an uncontrolled scenario with an average speed of 80 km/h.

However, since both fuel consumption and CO_2 emissions are related by an affine relationship given in (14), we get the relation:

$$\sum_{k=Mk_c}^{M(k_c+N_p)-1} \sum_{i=1}^{N} \bar{J}_{\mathrm{CO_2},i}(k) = NMN_p\delta_1 + \delta_2 \sum_{k=Mk_c}^{M(k_c+N_p)-1} \sum_{i=1}^{N} \bar{J}_{\mathrm{fuel},i}(k). \tag{17}$$

This means that the last two terms in the objective function suffice to represent reduction of fuel consumption, CO_2 emissions, and travel time.

In the case study of Section 5 we use a macroscopic traffic flow model METANET (Messmer and Papageorgiou, 1990) integrated with a microscopic emission and fuel consumption model (Ahn et al., 1999) described in Section 2. Note however that the MPC approach is generic and can also accommodate other, more complex traffic flow, emission, and fuel consumption models.

4. OPTIMIZATION PROBLEM

The control input $v_{\mathrm{lim,c},i}(k_c)$ in segment i at control time step k_c is related to the speed limit $v_{\mathrm{lim},i}(k)$ in segment i at simulation time step k through a zero-order-hold operation, i.e.,

$$v_{\mathrm{lim},i}(k) = v_{\mathrm{lim,c},i}\left(\left\lfloor \frac{k}{M} \right\rfloor \right) \tag{18}$$

where $\lfloor \cdot \rfloor$ denotes the floor operation. So, the objective function $J_{\mathrm{obj}}(k_c)$ in (15) depends on the state variables density $\rho_i(Mk_c + j)$, flow $q_i(Mk_c + j)$, space-mean speed $v_i(Mk_c + j)$, and queue length $w_o(Mk_c + j)$ for $j = 0, 1, \cdots, MN_p - 1$ and on the control inputs $v_{\mathrm{lim,c},i}(k_c)$, $v_{\mathrm{lim,c},i}(k_c + 1)$, $\cdots$, $v_{\mathrm{lim,c},i}(k_c + N_c - 1)$. This is because each element of the objective function is dependent on one or more of the state or input variables (see (13), (14), (16), and the traffic flow model (1)–(4)). Then, if we collect the above states into a big vector $\tilde{x}(k_c)$, and the control inputs into a big vector $\tilde{v}_{\mathrm{lim,c}}(k_c)$ we can write the objective function

$$J_{\mathrm{obj}}(k_c) = f(\tilde{x}(k_c), \tilde{v}_{\mathrm{lim,c}}(k_c)). \tag{19}$$

Then, the optimization problem of the MPC controller at time step k_c is

$$\min_{\tilde{v}_{\mathrm{lim,c}}(k_c)} f(\tilde{x}(k_c), \tilde{v}_{\mathrm{lim,c}}(k_c)) \tag{20}$$

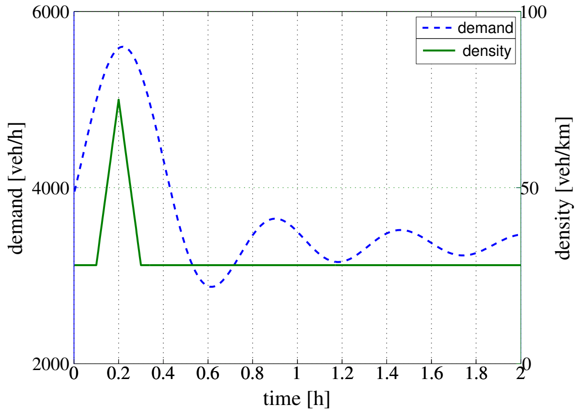


Fig. 4. Demand d_o at the origin and density ρ_d at the end of the freeway segments.

$$\text{s.t. } \tilde{x}(k_c) = \mathscr{M}(\tilde{x}_o(k_c), \tilde{v}_{\lim,i}(k_c), \tilde{d}(k_c)) \quad (21)$$
$$\tilde{x}(k_c) \geq 0 \quad (22)$$
$$v_{\text{low}} \leq \tilde{v}_{\lim,c}(k_c) \leq v_{\text{up}} \quad (23)$$
$$v_{\lim,c,i}(k_c + N_c + j) = v_{\lim,c,i}(k_c + N_c - 1) \text{ for all controlled segments } i \quad (24)$$

where $\tilde{x}_o(k_c)$ is the state of the network at time $t = k_c T_c$, $\tilde{d}(k)$ contains the evolution of the demand over the period $[k_c T_c, (k_c + N_p)T_c)$, $j = 0, \ldots, N_p - N_c - 1$, $\mathscr{M}(\cdot)$ is the state update equation of the system, v_{low} denotes the lower speed limit, and v_{up} denotes the upper speed limit.

Since the defined objective function is nonlinear and nonconvex function, we make use of multi-start sequential quadratic programming (SQP) (Pardalos and Resende, 2002) to numerically solve (20)–(24).

5. SIMULATION AND RESULTS

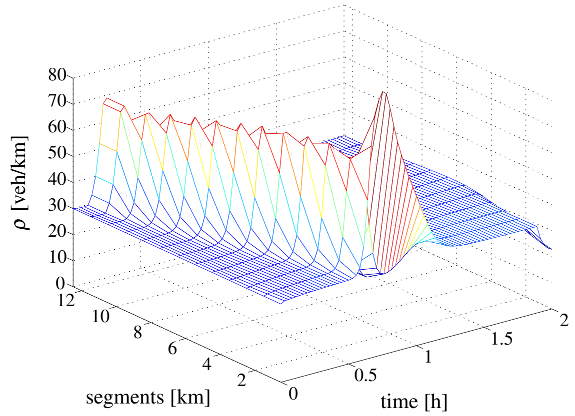
To demonstrate the approach we consider a 12 km two-lane freeway. The freeway is divided into 12 segments, where only the middle 6 segments are controlled with dynamic speed limits. In Fig. 4 we have presented the demand profile at the origin and a model of a shock wave at the end of the freeway. These two profiles provide one particular example of a traffic scenario where there is a shock wave that can cause traffic jams and a dynamic demand with a peak during the rush hour.

We consider a simulation period of 2 hours and implement the aforementioned traffic controller for 4 different scenarios, in particular, we investigate the following cases and objective functions:

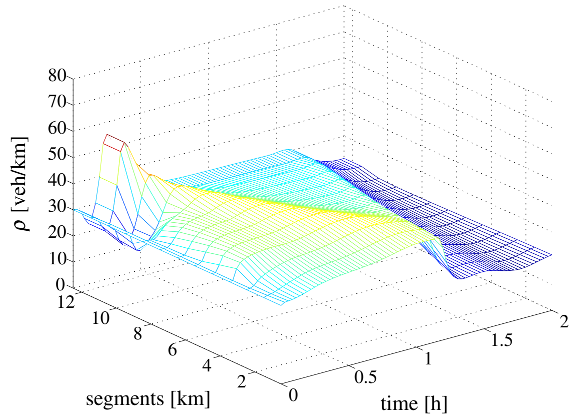
- S_1. uncontrolled
- S_2. controlled, total fuel consumption (or total CO_2 emission)
- S_3. controlled, total time spent , and
- S_4. controlled, total fuel consumption and total time spent

The simulation results are listed in Table 1. Under the considered traffic conditions, the results indicate that when the objective of the MPC controller is to reduce fuel consumption or CO_2 emission (S_2), both the CO_2 emissions and fuel consumption are reduced by 3.07%. But the total time spent is reduced only by 0.56%. This indicates that a control strategy that only focuses on fuel consumption or CO_2 emissions may not reduce the travel time significantly. However, when the objective of the controller is to reduce the travel time (S_3), the MPC controller reduces the total time spent, the fuel consumption, and the CO_2 emission by 20.01%, 14.15%, and 14.15% respectively. On the other hand, when the objective of the controller is set to be the weighted sum of fuel consumption (or CO_2 emissions) and total time spent (S_4), the controller results in a slight improvement of the emissions and fuel consumption from scenario S_3, and a better improvement of the travel time than in scenario S_2. These results indicate that under the given traffic conditions, reducing travel time can also have a positive effect on the reduction of the fuel consumption and there by the CO_2 emissions.

Since the improvement of the total time spent under scenario S_3 is significant, we depicted the traffic densities of the whole link in Fig. 5(b) in order to analyze the traffic phenomena in there. In order to compare the density profile of the TTS controlled case (S_3) with the uncontrolled case (S_1), we have also plotted the density profile of the link for the uncontrolled case in Fig. 5(a). Under the uncontrolled scenario (S_1), the shock wave created around the time $t = 0.25$ h propagates through the entire link upstream from segment 12 to segment 1 (see Fig. 5(a)). However, when an MPC controller is implemented to reduce the travel time (S_3) the shock wave is reduced and dissolves in time as it propagates upstream (see Fig. 5(b)), i.e. the controller creates relatively smooth traffic flow. Moreover, the peak of the shock wave at segment 12 of case S_3 is less than that of case S_1. This shows that the proposed MPC controller is able to either reduce or avoid the appearance of shock waves.



(a) S_1 uncontrolled case



(b) S_3 TTS controlled case

Fig. 5. Traffic density distribution

Table 1. Simulation results

Variables	S1:Uncontrolled	S2: Fuel (g%)	S3: TTS (g%)	S4: TTS + Fuel (g%)
	Control objectives			
TTS (veh·h)	2142.3	2130.2 (-0.56)	1713.6 (-20.01)	1749.1 (-18.35)
CO_2 (kg)	28368	27497 (-3.07)	24354 (-14.15)	24347 (-14.17)
Fuel (l)	10705.0	10376.0 (-3.07)	9190.2 (-14.15)	9187.6 (-14.17)

(g%) denotes the % change of the variables with respect to scenario S_1

The results above show that under the presence of chock wave and dynamic demand with peak during rush hour, MPC can still offer a balanced trade-off between reducing fuel consumption, emissions, and the travel time. The trade-off can be adjusted by changing the weight of the fuel consumption, emission, and total time spent terms in (15).

6. CONCLUSIONS

In this paper we have derived VT-macro, an integrated model for describing traffic flows, emissions, and fuel consumption. The integrated model can be used for on-line traffic control purposes and it is based on a combination of the macroscopic METANET traffic flow model and the microscopic emission and fuel consumption model VT-micro. The interface between the two submodels has been obtained by deriving equations to extract average accelerations from the METANET model and by adapting the VT-micro model to include these accelerations. We have also described how the new VT-macro model can be used in a model-based predictive control approach, and we have illustrated the resulting control approach with simulation experiments. The simulation study confirms that model-based traffic control with a multi-criteria objective function can be used to address the multi-faceted problem of reducing fuel consumption, emissions, and travel time. The experiments also show that the proposed approach can be used to obtain a balanced trade-off between the different performance criteria.

In our future work, we will validate, compare, and assess the performance of the VT-macro model. Moreover, we will consider different flow or emission models, implement other traffic control measures (such as ramp metering and route guidance), and study other more complex case studies.

ACKNOWLEDGEMENTS

Research supported by the Shell/TU Delft Sustainable Mobility program, the BSIK project “Transition towards Sustainable Mobility (TRANSUMO)”, the Transport Research Center Delft, and the European COST Action TU0702.

REFERENCES

K. Ahn and H. Rakha. The effects of route choice decisions on vehicle energy consumption and emissions. *Transportation Research Part D*, 13(3):151–167, May 2008.

K. Ahn, A. A. Trani, H. Rakha, and M. Van Aerde. Microscopic fuel consumption and emission models. In *Proceedings of the 78th Annual Meeting of the Transportation Research Board*, Washington DC, USA, January 1999. CD-ROM.

T. Bellemans, B. De Schutter, and B. De Moor. Model predictive control for ramp metering of motorway traffic: A case study. *Control Engineering Practice*, 14(7):757–767, July 2006.

C. M. Benedek and L. R. Rilett. Equitable traffic assignment with environmental cost function. *Journal of Transportation Engineering*, 124(1):16–22, January/February 1998.

P. G. Boulter, T. Barlow, I. S. McCrae, S. Latham, D. Elst, and E. van der Burgwal. Road traffic characteristics, driving patterns and emission factors for congested situations. Technical report, TNO Automotive, Department Powertrains-Environmental Studies & Testing, Delft, The Netherlands, 2002. OSCAR Deliverable 5.2.

E. F. Camacho and C. Bordons. *Model Predictive Control in the Process Industry*. Springer-Verlag, Berlin, Germany, 1995.

N. H. Gartner. Development of demand-responsive strategies for urban traffic control. In P. Thoft-Christensen, editor, *In Proceedings of the 11th IFIP Conference System Modelling and Optimization*, pages 166–174. New-York: Springer-Verlag, 1984.

A. Hegyi. *Model Predictive Control for Integrating Traffic Control Measures*. PhD thesis, Delft University of Technology, The Netherlands, February 2004.

A. Hegyi, B. De Schutter, and H. Hellendoorn. Model predictive control for optimal coordination of ramp metering and variable speed limits. *Transportation Research Part C*, 13 (3):185–209, June 2005.

J. Heywood. *Internal Combustion Engine Fundamentals*. McGraw-Hill, New York, 1988.

A. Kotsialos, M. Papageorgiou, C. Diakaki, Y. Pavlis, and F. Middelham. Traffic flow modeling of large-scale motorway networks using the macroscopic modeling tool METANET. *IEEE Transactions on Intelligent Transportation Systems*, 3(4):282–292, December 2002.

J. M. Maciejowski. *Predictive Control with Constraints*. Prentice Hall, Harlow, England, 2002.

A. Messmer and M. Papageorgiou. METANET: A macroscopic simulation program for motorway networks. *Traffic Engineering and Control*, 31(9):466–470, 1990.

L. Ntziachristos and Z. Samaras. Speed-dependent representative emission factors for catalyst passanger cars and influencing parameters. *Atmospheric Environment*, 34(27):4611–4619, March 2000.

M. T. Oliver-Hoyo and G. Pinto. Using the relationship between vehicle fuel consumption and CO_2 emissions to illustrate chemical principles. *Journal of Chemical Education*, 85(2): 218–220, February 2008.

P. M. Pardalos and M. G. C. Resende. *Handbook of Applied Optimization*. Oxford University Press, Oxford, UK, 2002.

G. H. Tzeng and C. H. Chen. Multiobjective decision making for traffic assignment. *IEEE Transactions on Engineering Management*, 40(2):180–187, May 1993.

M. van den Berg, A. Hegyi, B. De Schutter, and J. Hellendoorn. A macroscopic traffic flow model for integrated control of freeway and urban traffic networks. In *Proceedings of the 42nd IEEE Conference on Decision and Control*, pages 2774–2779, Maui, Hawaii, USA, December 2003.

S. K. Zegeye, B. De Schutter, J. Hellendoorn, and E. A. Breunesse. A model-based predictive traffic control approach for the reduction of emissions. In *Proceedings of the 10th TRAIL Congress*, Rotterdam, The Netherlands, October 2008.