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A model-based predictive traffic control approach for the reduction of emissions*

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A model-based predictive traffic control approach for the reduction of emissions

TRAIL Research School, Delft, October 2008

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Abstract

The main objective of this paper is to illustrate the applicability and potential advantages of model-based traffic control for the reduction of emissions. We investigate the impact of a model-based control strategy on emissions and traffic flow using model predictive control (MPC). We consider reduction of emissions and total time spent (TTS). The MPC controller is based on a car-following traffic flow model and an average-speed-based emission model. Moreover, we illustrate that a control strategy, that only addresses the improvement of traffic flow does not necessarily guarantee improvement in the level of emissions. We demonstrate that a traffic control strategy (such as MPC) addressing emissions and total time spent can result in a balanced reduction of emissions and total time spent.

Using simulation, we analyse the effects of different weighting combinations on the different emission gases of traffic flow and the TTS. We illustrate with a simulation example that the proposed traffic control approach can reduce both emissions and TTS. Simulation results show 11.1% reduction in average time spent, and 37.55% reduction in total average emission levels.

Keywords

Traffic management, emissions, model-based predictive control, optimisation

1 Introduction

Despite the improvements in transportation systems, the rise of fuel prices, and the imposition of more stringent environmental policies for emission levels, the demand for mobility and transportation is continuously increasing. Consequently roads are frequently congested, creating economical, social, and ecological challenges. Moreover, in recent epidemiological studies of the effects of combustion-related (mainly traffic-generated) air pollution, NO_2 was shown to be associated with adverse health effects (WHO, 2004; Schmidt & Schäfer, 1998). Furthermore, road traffic exhaust emissions account for 40% of volatile organic compounds, more than 70% of NO_x, and over 90% of CO in most European cities (Schmidt & Schäfer, 1998), and about 45% pollutants released in the US (National Research Council, 1995). Frequent and longer congested traffic conditions make this even worse.

There are several possible approaches to address these problems. Large-scale substitution of fossil oil by alternative fuels is a possible solution, but difficult to realise in the short to medium term. A second possible solution is enhancing vehicle technology. However, vehicle improvements seem to be approaching their limits (Kishi et al., 1996) and they alone cannot solve the problems. Furthermore, the limitations in the availability of land, the economical and environmental constraints make extending infrastructures a difficult solution. An alternative and promising solution is the implementation of intelligent transportation systems. Different traffic flow control measures (such as traffic signal, ramp metering, speed control, route guidance, etc.) can then be used to minimise the impact of traffic jams (such as longer travel times and emissions).

To the best of our knowledge, there are not many papers in the traffic control literature that explicitly aim on the reduction of emissions directly. Many papers deal with traffic control problems to improve traffic flow. They address problems related to reduction of congestion, improving safety, reducing total time travel, and the like. As an example, Hegyi et al. (2005) showed that integration of speed limit control and ramp metering can be used to reduce the total time spent (TTS). Similar work by Zhang et al. (2005) but using microscopic models shows similar results. But, both studies focus on the improvement of traffic flow. However, improvement in traffic flow does not necessarily guarantee reduced emission levels. As will be shown in this work, a controller that focuses only on reduction of the TTS can result in higher emissions than a controller that also takes emissions into account. This paper illustrates how to integrate both requirements so that a balanced trade-off is obtained.

In this paper we use a model-based control approach to reduce emissions while still improving the traffic flow. Particularly we implement Model Predictive Control (MPC) using a car-following model and an average-speed-based emission model. We use speed limit control to control a freeway network to improve the TTS and the total emissions. The results show that a control strategy with an objective of reducing emissions and improving traffic flow can have different impact on the traffic flow than when only concentrating on the improvement of the traffic flow.

The paper starts by discussing both the traffic and the emission models considered in this study in Section 2. In Section 3 the MPC control strategy is presented. Section 4 illustrates the particular example we considered for this study. Finally, Section 5 gives the conclusions drawn from the work.

2 Models

2.1 Traffic flow models

Traffic flow models can be divided into three classes, viz. macroscopic, microscopic, and mesoscopic. Macroscopic traffic models deal with the average traffic variables (such as average speed, average density, and average flow). On the other hand microscopic traffic models describe the behaviour of individual vehicles in the traffic flow. The position, speed, and acceleration of each vehicle are the states of such models. Mesoscopic traffic models describe the behaviour of each vehicle (microscopically) with macroscopic variables (such as link flows and link travel times). In other words mesoscopic models combine characteristics of both microscopic and macroscopic traffic flow models. For this study we use a microscopic traffic model, particularly car-following model. In this paper only the longitudinal kinematic behaviour of vehicles and drivers is considered.

Vehicle kinematics
The general longitudinal kinematic motion of the vehicles after discretisation is described by:

$$x_i(\ell+1) = x_i(\ell) + v_i(\ell)t_{\mathrm{s}} + 0.5a_i(\ell)t_{\mathrm{s}}^2 \tag{1}$$

$$v_i(\ell+1) = v_i(\ell) + a_i(\ell)t_{\mathrm{s}} \tag{2}$$

where x_i, v_i, and a_i are the position, speed, and acceleration of i^{th} vehicle in the network, ℓ is the simulation time step counter, while t_{s} is the sampling time of the discretised model. The acceleration in (1) and (2) is determined from the driver model described in the sequel. Moreover, the acceleration is saturated between minimum and maximum acceptable accelerations $a_{\min}$ and $a_{\max}$ respectively.

Longitudinal human driver behaviour
The speed and nature of the reaction of drivers is dependent on their headway time (or distance). The time headway is defined as the time difference between two consecutive vehicles to pass a certain location. This can be described as the time needed by the following vehicle to reach the current position of the leading vehicle with its current speed. Mathematically it can be given as:

$$t_{\mathrm{h}}(\ell) = \frac{x_{\mathrm{l}}(\ell) - x_{\mathrm{f}}(\ell)}{v_{\mathrm{f}}(\ell)} \tag{3}$$

where x_{l}, x_{f} are the positions of the leading and the following vehicle respectively, and v_{f} is the speed of the following vehicle. Depending on the time headway a vehicle can be either in car-following or free-flow mode. When the time headway is larger than the threshold time headway (e.g, 10 s), then the vehicle is said to be in free-flow mode. Whereas if the time headway is smaller than the threshold time headway, then the vehicle is in car-following mode.

In free-flow driving conditions the acceleration (or response) of a vehicle is determined by a constant multiple of the difference in the delayed reference speed (or speed limit) and delayed speed of the vehicle. Mathematically, this is described as:

$$a_i(\ell) = F\left(v_{\mathrm{ref},i}(\ell-\sigma) - v_i(\ell-\sigma)\right) \tag{4}$$

where F is a controller parameter, $v_{\mathrm{ref},i}$ is the speed limit (or reference speed) of the i^{th} vehicle, σ is the reaction delay[1] of the driver. In the car-following driving mode, where the time headway is smaller than the threshold time headway t_{tr}, the acceleration of the vehicle is determined using car-following models. There are various types of car-following models. A review of various car-following models can be found in Brackstone & McDonald (2000). In this paper we use the Gazis-Herman-Rothery (GHR) (Gazis et al., 1961) stimuli-response car-following model. In this model the reaction of the driver (in other words the acceleration of the vehicle) varies with the variation of its current speed, and the relative speed and position of the vehicle with respect to its predecessor vehicle (Brackstone & McDonald, 2000; Hoogendoorn & Bovy, 2001; Bong & Han, 2005). The model also takes in to account the delay in the reaction of the driver in the relative speed and position of the vehicle. The expression given below describes the relationship of the variables:

$$a_{\mathrm{f}}(\ell) = \alpha v_{\mathrm{f}}^{\beta}(\ell) \frac{(v_{\mathrm{l}}(\ell-d) - v_{\mathrm{f}}(\ell-d))}{(x_{\mathrm{l}}(\ell-d) - x_{\mathrm{f}}(\ell-d))^{\gamma}} \tag{5}$$

where α, β, and γ are model parameters, and d is the reaction delay of the driver.

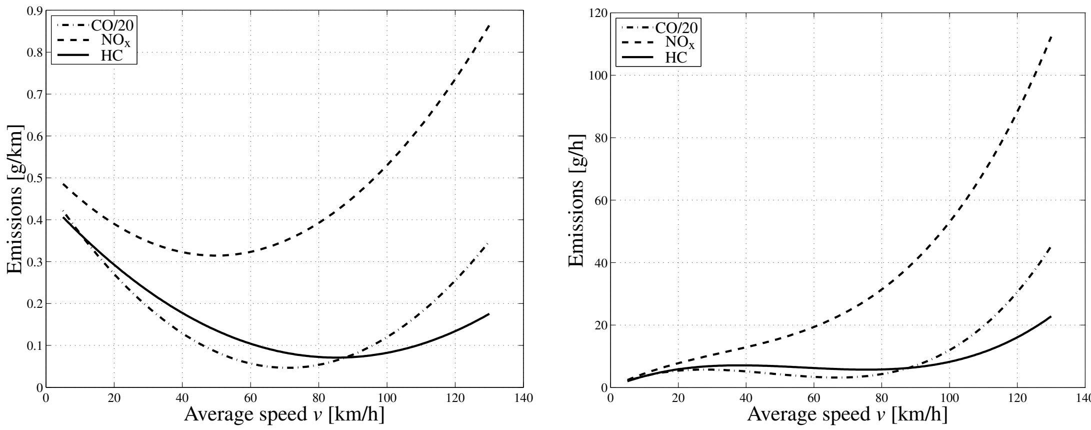
2.2 Traffic emission models

Traffic emission models calculate the emissions produced by vehicles based on the operating conditions of the vehicles. Emissions 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 models can be calibrated for every vehicle, or homogeneous vehicle categories. The main inputs to the emission models are the operating conditions of the vehicle (such as speed, acceleration, engine load) (Heywood, 1988). Emission modelling approaches can be either technology-based engineering modelling or traffic emission modelling.

Technology-based emission or/and fuel consumption models are very detailed models. These kind of models are developed for a specific vehicle (or engine) model (Heywood, 1988). Thus, such models are used for the assessment of new technological developments, and for regulation purposes (Heywood, 1988). Since these models are very detailed, they are difficult to use for on-line prediction or/and on-line estimation of emissions and fuel consumption of traffic flow. Therefore, we do not use such models for this study.

Traffic emission models are more simple, and they are developed for diverse collections of vehicles grouped in homogeneous categories. In general these models are calibrated based on the operating conditions of the vehicle in a traffic flow. Traffic emission models can be either *average-speed-based* or *dynamic*. For its simplicity of use, and for being a long established method (Boulter et al., 2002) we have used an average-speed-based model for this study. In principle the input for an average-speed-based model is the trip-based average speed, but in practise it is also common to use local speed inputs (Boulter et al., 2002). Moreover, using local speed inputs can give more accurate results. And thus we implemented the local speed input approach of the model.

[1]We assume that the reaction delay is an integer multiple of simulation time step.



(a) Emissions in g/km (b) Emissions in g/h

Figure 1: Average speed based emission model for petrol EURO 1 passenger cars, 1.4-2.0l

The model considered for this study is obtained from COPERT III (Ntziachristos & Samaras, 2000). Fig. 1(a) shows the model used for CO, NO_x, and HC emissions. The mathematical expressions for this model of each of the emissions are:

$$E_{CO}(v) = (0.001728v^2 - 0.245v + 9.617) \text{ [g/km]} \tag{6}$$

$$E_{NO_x}(v) = 10^{-4}(0.854v^2 - 85v + 5260) \text{ [g/km]} \tag{7}$$

$$E_{HC}(v) = 10^{-4}(0.521v^2 - 88.8v + 4494) \text{ [g/km]} \tag{8}$$

where v is the average speed and E_{CO}, E_{NO_x} and E_{HC} denote the emission levels of carbon monoxide (CO), oxides of nitrogen (NO_x), and hydrocarbons (HC) in grams per kilometre respectively.

As the output of the emission model in (6)-(8) is given in g/km, we changed the expressions into emission functions which results in emissions in g/h. This is done by multiplying the expressions by the average speed v. This model makes computation of emission levels of each vehicle simpler. We can get the emission levels at each simulation step by multiplying the output of the model with the simulation time step. This model can then be used to get second-by-second emissions of a vehicle in a network. The new expressions of the model have a structure that is similar to the model of Ahn et al. (1999) when the acceleration is zero. But, since the model of Ahn et al. (1999) is developed considering acceleration into account, the corresponding coefficients of the model are different. The plots of the transformed equations are given in Fig. 1(b).

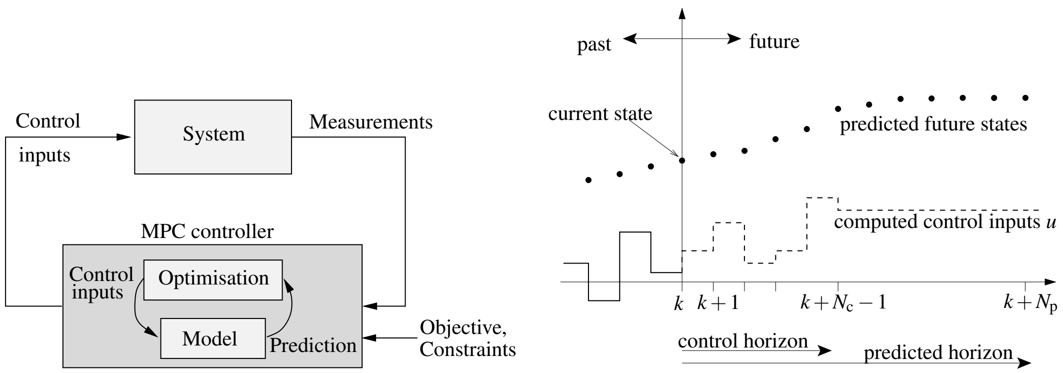
3 Model Predictive Control

3.1 Philosophy of model predictive control

The basic concept of Model Predictive Control (MPC) (Maciejowski, 2002; Camacho & Bordons, 1995) lies in the optimisation of control inputs based on prediction and a moving horizon. MPC uses an on-line optimisation method, based on the measurement of current and future predicted evolution of the system states. Using a model of the system and numerical optimisation, it determines a sequence of control inputs that optimise a performance criterion over the given future time horizon (i.e. from control time k up to $k+N_{\mathrm{p}}$). However, only the first control input is applied for the system in a moving horizon concept[2]. At every time step the process is repeated.

This concept in depicted in the schematic diagram given in Fig. 2. Fig. 2(a) illustrates the interrelationship of the traffic system and MPC controller, and Fig. 2(b) depicts the concepts of prediction and control horizons. We consider both the traffic system and MPC controller in discrete time. The discrete control time counter k, is an integer divisor of the discrete simulation time counter ℓ (i.e. $\ell = Mk$, where $M \in \mathbb{N}^{+}$). A measurement of the traffic states is made at every M simulation time steps (see Fig. 2(a)). In other words, after a control signal is applied for M simulation time steps, a new measurement of the states of the system is undertaken and the MPC controller generates and applies new control inputs by predicting the evolution of the system states from the current time k up to the $k+N_{\mathrm{p}}$ future time (see Fig. 2(b)).

The main advantage of MPC is its ability to take constraints into account and that it can be used for nonlinear systems. Its main limitation emanates from the computation time required by the optimisation process. To alleviate the computational problems several methods can be used. In order to limit the number of variables to be optimised, a control horizon $N_{\mathrm{c}} \leq N_{\mathrm{p}}$ is defined after which the control input is kept constant, i.e. $u(k+j) = u(k+j-1)$ for $j = N_{\mathrm{c}}, \cdots, N_{\mathrm{p}}-1$, where $N_{\mathrm{c}} \leq N_{\mathrm{p}}$.



(a) Schematic representation (b) Prediction and control horizon

Figure 2: Conceptual representation of model predictive control

3.2 MPC for traffic and emission control

In this study we use MPC to control the traffic flow using speed limits. We investigate the impact of speed limit control on the improvement of the total time spent (TTS) and the total emissions in a traffic network. The model of the optimisation includes both a traffic flow model and an emission model. As models we could use the ones presented in Section 2. Note however that MPC is a modular control design method. As a consequence, it can also accommodate other, more complex traffic models.

[2]At each control time step only the first sample of the optimal control input is applied to the system; afterward the time axis is shifted one control sample time step. Then, based on the new states and control inputs of the system, new set of optimal control inputs are generated. Ones again the first control input is applied. This process is repeated until the end of the simulation time.

We update the control action every *varntc* time units, where t_{c} is called the control time step and assumed to be an integer multiple of the simulation time step t_{s}: $t_{\mathrm{c}} = Mt_{\mathrm{s}}$, where M is a positive integer number. Therefore, the controller time step counter k is an integer divisor of the simulation time counter ℓ. At time $t = M \cdot t_{\mathrm{c}} = \ell \cdot t_{\mathrm{s}}$ they are related by $\ell = Mk$. At control time step k, the MPC controller predicts the evolution of the traffic flow and emission levels in the network for the time period $[k \cdot t_{\mathrm{c}},\ (k + N_{\mathrm{p}} \cdot t_{\mathrm{c}})$, and it optimises the speed limit control $u_{\mathrm{s}} = [u^T(k),\ u^T(k+1),\ \cdots, u^T(k+N_{\mathrm{c}}-1)]^T$ in such a way that the objective function

$$J(k) = \lambda_1 \sum_{j=1}^{MN_{\mathrm{p}}} \mathscr{N}(\ell(k)+j)t_{\mathrm{s}} + \lambda_2 \sum_{j=1}^{MN_{\mathrm{p}}} \sum_{i \in \mathscr{V}(\ell(k)+j)} T_{\mathrm{E},i}(\ell(k)+j) + \lambda_3 \sum_{j=0}^{N_{\mathrm{c}}-1} \|u(k+j) - u(k+j-1)\|_2^2 \quad (9)$$

is reduced. Here $\lambda_n \geq 0$, for $n = 1,2,3$ are weighting coefficients, $\mathscr{N}(\ell)$ denotes the number of vehicles in the network at time $t = \ell \cdot t_{\mathrm{s}}$, and $\mathscr{V}(\ell)$ denotes the set of vehicles present in the network at time $t = \ell \cdot t_{\mathrm{s}}$. Moreover,

$$T_{\mathrm{E},i}(\ell) = \begin{cases} \left(\mu_1 E_{\mathrm{CO}}(v_i(\ell)) + \mu_2 E_{\mathrm{NO_x}}(v_i(\ell)) + \mu_3 E_{\mathrm{HC}}(v_i(\ell))\right) v_i(\ell) t_{\mathrm{s}} & \\ \qquad\qquad \text{if vehicle } i \text{ is in the network at time } t = \ell \cdot t_{\mathrm{s}} & \\ 0 \qquad\qquad \text{otherwise} & \end{cases}$$

corresponds to the total weighted emissions of vehicle i at time $t = \ell \cdot t_{\mathrm{s}}$, and $\mu_i \geq 0$, $n = 1,2,3$ are the weighting values for the different emission gases. The last term in (9) is a penalty term for fluctuations of the control inputs.

Next, only the first optimal control input $u_{\mathrm{s}}^*(1) = u^*(k)$ of the optimal control input sequence $u_{\mathrm{s}}^* = [u^T(k)^*,\ u^T(k+1)^*,\ \cdots, u^T(k+N_{\mathrm{c}}-1)^*]^T$ is applied to the system. At the next control time step $k+1$, the same process is repeated.

3.3 Optimisation method

One of the bottlenecks in MPC control approach is the extensive optimisation and the resulting computational requirements. The MPC optimisation problem considered for this study is nonlinear. Then the objective function, which is a function of the system states, is also a nonlinear and nonconvex function. Thus a proper choice of optimisation technique has to be made in order to obtain feasible optimal control values. Owing to the nonconvex nature of the objective function, global or multi-start local optimisation methods are required. In our case multi-start sequential quadratic programming (SQP) (Pardalos & Resende, 2002), pattern search (Audet & Dennis Jr., 2007), generic algorithms (Davis, 1991), or simulated annealing (Eglese, 1990) can be used.

4 Case Study

In this section we demonstrate the applicability of the strategies aforementioned above on a simple case study. We consider this simulation benchmark to investigate the effect of the control strategy. The layout of the freeway, the performance criterion and simulation results are given in the subsequent subsections.

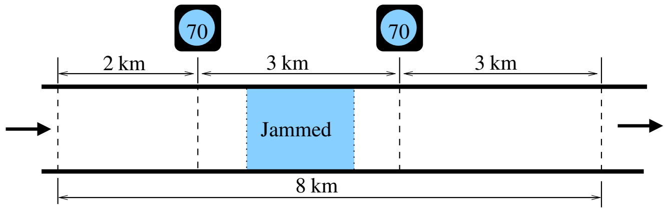


Figure 3: Layout of the case study

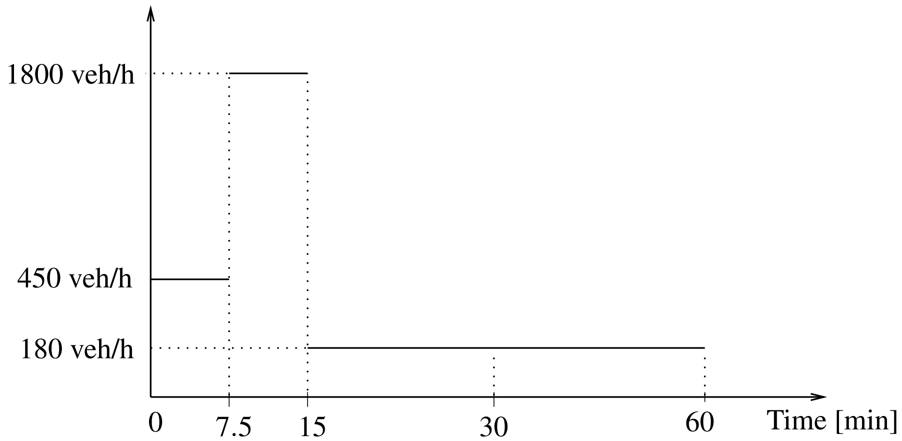


Figure 4: Demand profile

4.1 Traffic freeway layout

We have considered a single-lane one-way 8 km freeway. As shown in Fig. 3, the roadway is divided into three sections, and two speed limit controls are applied in the last two sections. The section of the freeway from 3.5km to 5.5km is assumed to be congested. When the system is initialised the demand varies over the whole span of the simulation time. We have considered the same demand for all the different cases considered in this study. The demand profile is depicted in Fig. 4. It illustrates the variation of the number of vehicle entering the network with respect to time. For instance, in the first 7.5 minutes (=1/8h), the number of vehicles entering the network (freeway) is computed as $450\text{veh/h} \times 1/8\text{h} \approx 57\text{vehicles}$.

Moreover, the parameters that we have used for the MPC controllers are tabulated in Table 1.

4.2 Performance criterion

In this case study we have considered the performance criterion defined in (9). We have considered different weighting values to analyse the effects of different control policies on emissions and traffic flow. The combinations considered in this study are given in Table 2. Before, weighting the TTS, emissions, and change in control input, we first normalised both TTS and emissions with a typical values at an average speed of 80 km/h. The average speed is chosen as the average of the possible minimum and maximum speed limit controls. At this typical speed, the time spent and total emissions of a single vehicle to complete the 8 km freeway are computed. These values are then used to normalise both the TTS and emissions components of the objective function.

For solving the MPC optimisation problem we have adopted a multi-start sequential

Table 1: MPC controller parameters

MPC Parameters	Values	Remarks
T_{sim}	60 min	Simulation time
N_{p}	10 min	Prediction horizon
N_{c}	2 min	Control horizon
t_{c}	1 min	Control time step
t_{s}	1 s	Simulation time step
$v_{\max}$	120 km/h	Maximum speed limit
$v_{\min}$	40 km/h	Minimum speed limit

Table 2: Simulation results for different cases

Cases	Weighting			Simulation results				
				Average	Average emission (g)			
	λ_1	$\lambda_2(\mu_1,\ \mu_2,\ \mu_3)$	λ_3	time spent (h)	CO	NO_x	HC	Total average emission
case 1	0	0	0	0.12769	37.593	5.2078	1.3373	44.1381
case 2	1	0	0.01	0.07013	42.673	5.9496	1.1104	49.733
case 3	0	1(1, 1, 1)	0.01	0.11352	22.538	4.107	0.9786	27.6236
case 4	1	1(1, 1, 1)	0.01	0.11341	22.487	4.1008	0.9772	27.565
case 5	1	1(0.9, 1.5, 0.6)	0.01	0.12513	24.038	4.0360	1.0866	29.1606
case 6	0	1(0.9, 1.5, 0.6)	0.01	0.12513	24.039	4.0358	1.0866	29.1614

quadratic programming (SQP) (Pardalos & Resende, 2002) optimisation method. More specifically, we have used `fmincon` command of the Matlab optimisation toolbox.

4.3 Simulation results

Two terms are defined to analyse the simulation results, viz. average time spent and average emissions. The average time spent (ATS) is defined as the total time spent of all the vehicles in the network divided by total number of vehicles. This reflects the average time spent by each vehicle in the network. Similarly the average emissions (AE) is the ratio of the total emissions of all vehicles in the network and the total number of vehicles in the network. This also reflects the average emissions by each vehicle in the network. Mathematically the two expressions are given as:

$$\mathrm{ATS} = \frac{\mathrm{TTS}}{\mathcal{N}_{\mathrm{T}}} \tag{10}$$

$$\mathrm{AE}_g = \frac{\mathrm{TE}_g}{\mathcal{N}_{\mathrm{T}}} \tag{11}$$

where TTS is the total time spent, TE_g denotes the total emissions of gas type g, and $\mathcal{N}_{\mathrm{T}}$ denotes the total number of vehicles that entered in the network in the simulation period.

The system has been simulated for a simulation period of 1 h. This has been done for uncontrolled and controlled scenarios. The results of the simulation are shown in Table 2. As it can be seen from the table, the average time spent (ATS) and the total average emissions (TE) are 0.12769 h and 44.1381 g respectively when the system is not controlled (case 1). When an MPC controller with an objective function of reducing TTS (case 2) is used, the ATS has reduced by 45.1%, while total AE has increased by 12.68%. With the same controller, but with an objective of reducing emissions (case 3), the ATS has reduced by 11.1% and the total AE has reduced by 37.42%. The ATS in case 3, is larger than the ATS in case 2. This shows that controlling the total time spent or the total emissions alone have negative effects on emissions and traffic flow respectively. That is to say that neither a reduction in TTS does imply reduced emissions nor does a reduction in total emissions imply a reduced TTS.

In case 4, the weighted sum of TTS and total emissions is considered as a cost function of the optimisation in the MPC controller. The change in TTS and total AE is insignificant relative to case 3. But it has significant improvement as compared to case 1, and case 2. The changes are also more noticeable when the weighting factors are changed. Comparing case 2, case 5, and case 6 we observe that the controller with TTS as objective causes higher emission levels. Moreover, the controller with an objective of reducing TTS and total emissions reduces the ATS by 11.18% (compare case 1 and case 4) and the total AE by 37.55%. It is also possible to observe from the table that by assigning different weighting to the specific emissions gases, the relative level of emissions of each gas can be influenced.

The results indicate that the objective of reducing emissions and TTS are two conflicting requirements in the traffic control system. It is difficult to get lowest emissions without restricting the traffic flow or vice versa. This indicates that higher flows (or speeds) do not guarantee reduced emissions. To make the matter worse, the results in case 4, and 5, or case 3, and 6, indicate that the requirement of reducing total emissions is difficult. The minimum value of the different traffic emissions are attained at different traffic speeds. This makes it difficult to make a decision on the selection of better speed limit to optimally reduce the level of the emissions. Reducing the total emissions may have more influence on some gases than others. In the report of WHO (WHO, 2004), it is shown that NO_x has a stronger adverse health effect than the other gases. However, gases like CO, have a bad effect in the long run. Therefore, from the study above, we see that making choices on the gases to control, and also choices between emission levels and traffic flow is a difficult task. However, by assigning the relative weight (policies) on the different emissions, and TTS it is possible to use a model-based traffic control to set the optimal speed limit which can result in a balanced trade-off of the conflicting requirements.

5 Conclusions and Future Work

We have discussed the main challenges of traffic flow and its effects on the economy, the environment, and the society. We proposed a model-based traffic flow control to reduce both emissions and total time spent, or at least to provide a balanced trade-off between these performance indicators. We have presented the approach using a car-following traffic flow model and an average speed emissions model. A case study based on a single-lane one-way traffic road has been made. Two speed limit controls were applied to show how MPC can be applied and to demonstrate the possible solutions MPC can offer for mobility and environmental challenges.

We have discussed the possible conflicting requirement of the demand for transportation and the environmental constraints. Based on simulation results, we have shown that the focus on the reduction of total time spent (TTS) alone cannot meet the requirement of reducing emissions. The simulation results suggest that emission reduction and traffic flow improvement can also be attained by proper definition of the objective function of the MPC controller. A 37.55% reduction of total average emissions and 11.1% reduction of average time spent has been obtained from the simulation study.

In future work we will consider more extensive case studies and investigate implementation of constraints on the emission levels, and integration of speed limit control and ramp metering for the reduction of emissions and of the total time spent.

Acknowledgements

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