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Model-Based Traffic Control for the Reduction of Fuel Consumption, Emissions, and Travel Time

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Abstract

In this paper we use a model-based traffic control approach to determine dynamic speed limits with the aim of reducing fuel consumption and emissions, while still guaranteeing small travel times. The approach we propose is based on model predictive control (MPC). MPC is a model-based control design method that combines prediction and on-line optimization of a performance criterion over a given time horizon to determine appropriate control inputs. MPC allows the inclusion of constraints on inputs and outputs, and it can handle changes in the system parameters by using a moving horizon approach, in which the model and the control strategy are updated regularly. We consider reduction of the total fuel consumption, total CO emissions, and total time spent in the traffic network. For the MPC controller we use a microscopic car-following traffic flow model and a microscopic emission and fuel consumption model. Based on simulations we demonstrate that a traffic control strategy (such as MPC) addressing total fuel consumption, total emissions, and total time spent can result in a balanced reduction of all the performance measures, by considering their weighted combinations as the overall performance criterion.

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 [21, 22]. 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 [21], and for about 45% pollutants released in the US [19]. 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 it is not feasible to realize in the short to medium term. A second possible solution is enhancing vehicle technology. However, vehicle improvements seem to be approaching their limit [16] and they alone cannot solve the problems. Furthermore, the limitations in the availability of land, and the economical and environmental constraints often make extending infrastructures infeasible. An alternative and promising solution is the implementation of intelligent transportation systems [17, 23]. Different traffic control measures (such as traffic signal, ramp metering, speed control, route guidance, etc.) can then be used to minimize 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 at the reduction of emissions directly. Many papers either study the effect of different traffic assignment solutions on emissions and fuel consumption [1, 8, 9] or deal with traffic control problems to improve traffic flow [13, 23]. Most traffic control papers address problems related to the reduction of congestion, improving safety, reducing total time travel, and the like. As an example, Hegyi et al. [13] showed that integration of speed limit control and ramp metering can be used to reduce the total time spent (TTS). Related work by Zhang et al. [23] 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 or fuel consumption levels. As will be shown in this paper, a controller that focuses only on the reduction of emissions and fuel consumption does not necessarily guarantee reduced travel times. Therefore, 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 fuel consumption and emissions while still improving the traffic flow. We implement model predictive control (MPC) using a car-following model and a dynamic VT-micro fuel consumption and emission model. We use dynamic speed limit control to control a freeway network to improve the total fuel consumed, total CO emission level, and TTS.

The paper starts by discussing traffic flow and emission fuel consumption 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 [15]. 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 behavior 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 behavior of each vehicle (microscopically) using 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, in particular a car-following model. Note that in this paper only the longitudinal kinematic behavior of vehicles and drivers is considered. However, the proposed approach is generic and also valid for other more complex models that also include lane changing behavior.

Vehicle kinematics

The general longitudinal kinematic motion of the vehicles after discretization is described by

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

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

where $x_i(k)$, $v_i(k)$, and $a_i(k)$ are respectively the position, speed, and acceleration of the i^{th} vehicle in the network at time $t = k \cdot t_\mathrm{s}$. Here, k is the simulation time step counter, while t_s (e.g. $t_s = 1$ s) is the sampling time of the discretized model. The acceleration in Equations (1)–(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}.

Longitudinal human driver behavior

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 that 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 this can be expressed as

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

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 t_{tr}(e.g., $t_{\text{tr}} = 10\,\text{s}$), then the vehicle is said to be in free-flow mode. However, if the time headway is smaller than the threshold time headway, then the vehicle is in a car-following mode.

In free-flow driving conditions the acceleration 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

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

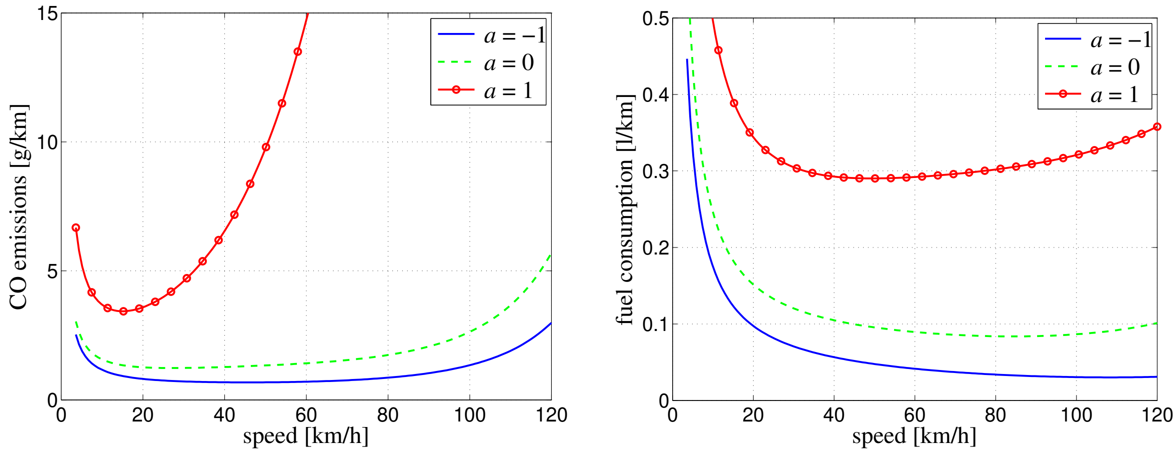
where F is a controller parameter (typically in the range 0.01-0.4), $v_{\text{ref},i}$ is the speed limit (or reference speed) of the i^{th} vehicle and, σ is the reaction delay of the driver. Here, we assume that the reaction time is an integer multiple of simulation time step. In the car-following 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 [6]. In this paper we use the Gazis-Herman-Rothery (GHR) [12] 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 [4, 6, 15]. The model also takes into account the delay in the reaction of the driver in the relative speed and position of the vehicle. The following expression describes the relationship of the variables

$$a_{\text{f}}(k) = \alpha v_{\text{f}}^{\beta}(k) \frac{\left(v_{\text{l}}(k-\sigma) - v_{\text{f}}(k-\sigma)\right)}{\left(x_{\text{l}}(k-\sigma) - x_{\text{f}}(k-\sigma)\right)^{\gamma}} \tag{5}$$

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

2.2 Traffic 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. 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. The main inputs to the models are the operating conditions of the vehicle (such as speed, acceleration, engine load) [14].



(a) CO emissions

(b) Fuel consumption

Figure 1: CO emissions and fuel consumption curves of a vehicle as a function of the speed for acceleration $a \in \{-1, 0, 1\}$ m/s.

Traffic emission and fuel consumption models are developed for diverse collections of vehicles grouped in homogeneous categories. Traffic emission and fuel consumption models can be either *average-speed-based* or *dynamic*. Average-speed-based models are simple to use and they are long established methods [5]. However, since such models neglect the dynamics of the speed of the vehicles, the estimates are relatively inaccurate [1, 5]. On the other hand, dynamic (also called microscopic) emission and fuel consumption models use the instantaneous speed and acceleration of individual vehicles in the traffic fleet [2]. For this study we use the VT-micro [2] dynamic emission and fuel consumption model.

VT-micro [2] is a microscopic dynamic model that yields emissions and fuel consumption using second-by-second speed and acceleration of individual vehicles. The model has the form

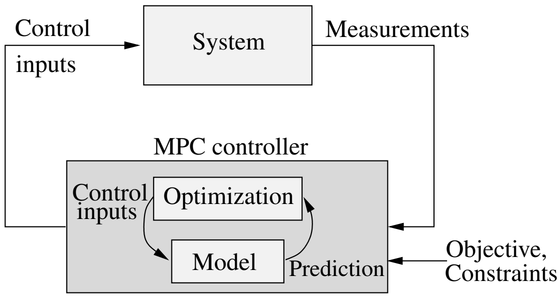
$$J_y(k) = \exp\left(\tilde{v}^T(k) P_y \tilde{a}(k)\right) \tag{6}$$

where J_y is the estimate or prediction of the variable $y \in \{\mathrm{CO}, \mathrm{NO_x}, \mathrm{HC}, \text{fuel consumption}\}$, with the operator $\tilde{\cdot}$ defining the vectors of the speed v [km/h] and the acceleration a [km/h^2] as $\tilde{v}(k) = \left[1 \; v(k) \; v^2(k) \; v^3(k)\right]^T$ and $\tilde{a}(k) = \left[1 \; a(k) \; a^2(k) \; a^3(k)\right]^T$ during the time period $[k \cdot t_\mathrm{s}, (k+1) \cdot t_\mathrm{s}]$, and P_y denotes the model parameter matrix for the variable y. The values of the entries of P_y can be found in [2]. Figure 1(a) and Figure 1(b) portray some CO emissions and fuel consumption curves generated using the VT-micro model.

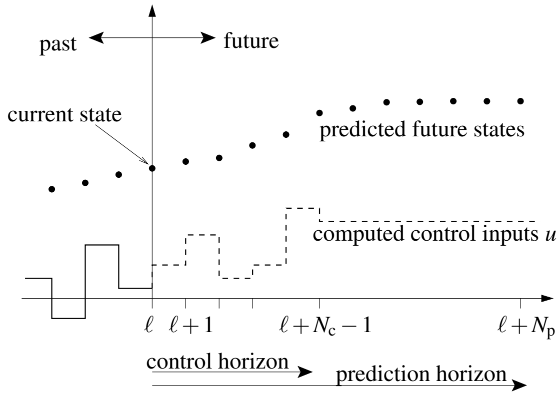
3 Model Predictive Control

3.1 Philosophy of model predictive control (MPC)

The basic concept of Model Predictive Control (MPC) [7, 18] lies in the optimization of control inputs based on prediction and a moving horizon approaches. An MPC controller uses an on-line optimization method, based on the measurement of current and future predicted evolution of the system states. Using a model of the system and numerical optimization, it determines a sequence of control inputs that optimize a performance criterion over a given future time horizon (i.e. from control step ℓ up to



(a) Schematic representation



(b) Prediction and control horizon

Figure 2: Conceptual representation of model predictive control (MPC).

$\ell+N_p$). However, only the first control input is applied for the system in a moving horizon concept, i.e. 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 time step. Then, based on the new states and control inputs of the system, a new sequence of optimal control inputs is generated. Once again the first control input is applied. At every control time step the process in repeated. This process is repeated until the end of the simulation time.

Figure 2(a) illustrates the interrelationship of the traffic system and MPC controller, and Figure 2(b) depicts the concepts of prediction and control horizons. We consider both the traffic system and the MPC controller in discrete time. Recall that t_s represents the sampling time. We define the control time step t_c (a typical value is $t_c = 1$ min). For the sake of simplicity we assume that $t_c = M \cdot t_s$, for some positive integer M. Therefore, at time $t = \ell \cdot t_c = k \cdot t_s$ the controller time step counter ℓ is an integer divisor of the simulation time counter k. They are related by $k(\ell) = M \cdot \ell$. A measurement of the traffic states (such as position, speed, acceleration, etc.) is made every t_c time units and the traffic control measures (such as speed limits, ramp metering rates, etc.) will be applied for the next t_c time units (see Figure 2(a)). In other words, after a control signal is applied for M sample steps of t_s time units, a new measurement of the states of the traffic 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 $t = \ell \cdot t_c$ up to $t = (\ell+N_p) \cdot t_c$ (see Figure 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 optimization process. To alleviate the computational problems several methods can be used (e.g. introducing control horizon). In order to limit the number of variables to be optimized, thereby to improve computation speed, a control horizon $N_c \leq N_p$ is defined after which the control input is kept constant, i.e. $u(\ell+j) = u(\ell+j-1)$ for $j = N_c, \dots, N_p - 1$.

3.2 MPC for traffic control

Besides the difference in the effects of traffic speed on emissions, fuel consumption, and total time spent, the minimum values of the traffic emissions, fuel consumption, and travel time are attained at different traffic speeds. This makes it difficult to decide which speed limit to select 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 [22], it is shown that NO_x has a stronger adverse health effect than the other gases. However, gases like CO, have adverse effect in the long run. By assigning relative weight (policies) on the different emissions, and total time spent (TTS) it is possible to use model-based traffic control to set the optimal speed limit which can result in a balanced trade-off of the conflicting requirements.

In this study we use an MPC controller to control the traffic flow using speed limits. We investigate the impact of speed limit control on the improvement of the total CO emissions, total fuel consumption, and TTS in a traffic network. The model of the optimization accommodates both a traffic flow model and an emission and fuel consumption model. As prediction model we could use the models presented in Section 2. However, note that the MPC approach is generic and can also accommodate other, more complex traffic flow and emission models.

At control time step ℓ, the MPC controller predicts the evolution of the traffic flow and the emission levels in the network over the time interval $\left[t_\mathrm{c}\cdot\ell, t_\mathrm{c}\cdot(\ell+N_\mathrm{p})\right]$ and it optimizes the speed limit control sequence $u(\ell), u(\ell+1), \ldots, u(\ell+N_\mathrm{c}-1)$ in such a way that the objective function is reduced. After the optimal control input sequence $u^*(\ell), u^*(\ell+1), \ldots, u^*(\ell+N_\mathrm{c}-1)$ has been computed, the first sample $u^*(\ell)$ is applied to the system until the next control step $\ell+1$. Subsequently, whole process is repeated all over again.

As an objective function we could for example consider the following expression. Note however that MPC is generic as regards the choice of the performance criteria, and so other objective functions could also be considered instead.

$$\begin{aligned}
J(\ell) = {} & \frac{\lambda_1}{\mathrm{TTS}_\mathrm{nominal}} \sum_{j=1}^{MN_\mathrm{p}} \mathscr{N}(k(\ell)+j)t_\mathrm{s} \\
& + \frac{\lambda_2}{\mathrm{TCO}_\mathrm{nominal}} \sum_{j=1}^{MN_\mathrm{p}} \sum_{i=1}^{\mathscr{N}(k(\ell)+j)} J_{\mathrm{CO},i}(k(\ell)+j)t_\mathrm{s} \\
& + \frac{\lambda_3}{\mathrm{Tfuel}_\mathrm{nominal}} \sum_{j=1}^{MN_\mathrm{p}} \sum_{i=1}^{\mathscr{N}(k(\ell)+j)} J_{\mathrm{fuel},i}(k(\ell)+j)t_\mathrm{s} \\
& + \frac{\lambda_4}{\mathrm{T}\Delta U_\mathrm{nominal}} \sum_{j=0}^{N_\mathrm{c}-1} \|u(\ell+j)-u(\ell+j-1)\|_2^2
\end{aligned} \tag{7}$$

where $\lambda_n \geq 0$ for $n = 1,2,3,4$ are weighting coefficients, $\mathscr{N}(k)$ denotes the number of vehicles at time $t = k\cdot t_\mathrm{s}$, and $J_{\mathrm{CO},i}(k)$ and $J_{\mathrm{fuel},i}(k)$ respectively denote the CO emissions, and fuel consumption of the i^th vehicle in the network or in a queue at time $t = k\cdot t_\mathrm{s}$. Moreover, the last term in the objective function denotes a penalty term for the fluctuation of the speed limit control. Note that each term in the objective function contains a normalization factor consisting of a "nominal" value for respectively the total time spent ($\mathrm{TTS}_\mathrm{nominal}$), the total CO emission ($\mathrm{TCO}_\mathrm{nominal}$), total fuel consumption ($\mathrm{Tfuel}_\mathrm{nominal}$), and a measure for the total speed limit difference ($\mathrm{T}\Delta u_\mathrm{nominal}$) (see also Section 4.2 for an example of how to compute these normalization factors).

3.3 Optimization method

One of the bottlenecks in the MPC control approach is the extensive optimization and the resulting computational requirements. The MPC optimization problem considered for this study is nonlinear and nonconvex. Thus a proper choice of an optimization 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 optimization methods are required. In our case multi-start sequential quadratic

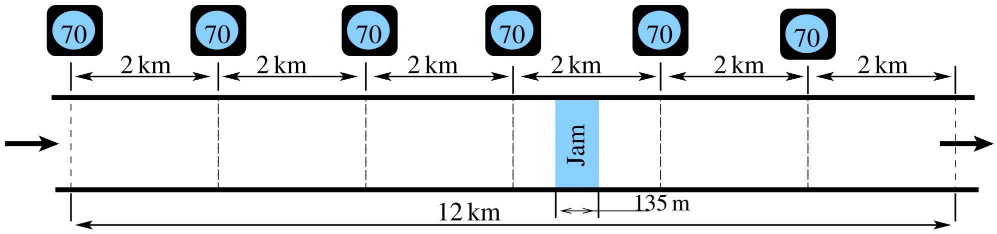


Figure 3: Layout of the case study.

programming [20], pattern search [3], generic algorithms [10], or simulated annealing [11] can be used.

4 Case Study

In this section we demonstrate the applicability of the MPC traffic control strategy described in Section 3 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.

4.1 Traffic freeway layout

We consider a single-lane one-way 12 km freeway. As shown in Fig. 3, the roadway is divided into six sections and each section is controlled with a dynamic speed limit control. We conduct the simulation experiment for half an hour ($t_{\text{duration}} = 0.5\,\text{h}$). At the beginning of the simulation, the segment of the freeway from 6.8 km to 6.935 km is assumed to be congested. The traffic demand varies over the whole span of the simulation time (see Fig. 4). The profile of the demand depicted in Fig. 4 is defined as

$$d_{\text{o}}(k) = \begin{cases} (0.024 + 0.057\text{sinc}(0.001k - \pi/4))t_{\text{s}} & \text{for } 0 \le k \le \dfrac{3N_{\text{sim}}}{4} \\ 0 & \text{for } k > \dfrac{3N_{\text{sim}}}{4} \end{cases} \tag{8}$$

where $\text{sinc}(x) = \sin(\pi x)/(\pi x)$, $t_s = 1$ s is the simulation sampling time, and $N_{\text{sim}} = 1800$ denotes the number of simulation time steps.

The setup is simulated for three different cases. In the first case (**S1**) we simulate the setup for uncontrolled traffic flow. The TTS, total CO emissions, and total fuel consumptions resulted from the simulation are given in the first row of Table 1. In the second and the third simulation we deal with controlled traffic flow, i.e. the scenarios are:

S2. controlled traffic flow with the objective of reducing both total CO emissions and total fuel consumption, i.e. $\lambda_1 = 0$, $\lambda_2 = \lambda_3 = 1$, and $\lambda_4 = 0.01$, and

S3. controlled traffic flow with the objective of reducing total CO emissions, total fuel consumption, and total time spent, i.e. $\lambda_1 = \lambda_2 = \lambda_3 = 1$, and $\lambda_4 = 0.01$.

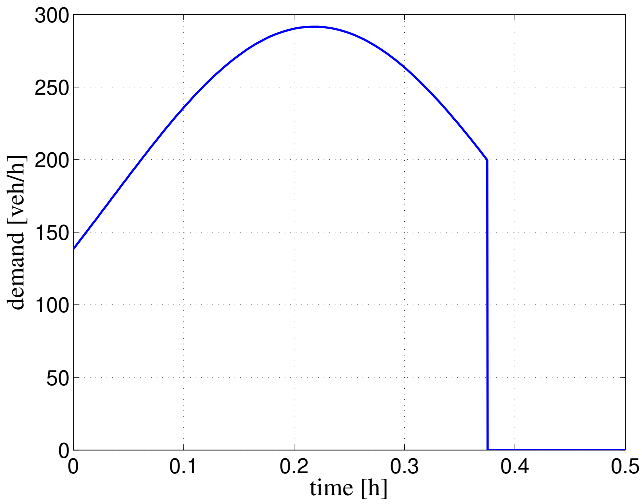


Figure 4: Demand profile.

4.2 Performance criterion

In this case study we have considered the performance criterion defined in Equation (7). The normalization factors $\text{TTS}_{\text{nominal}}$, $\text{TCO}_{\text{nominal}}$, and $\text{Tfuel}_{\text{nominal}}$ were computed by simulating the traffic system for the 12 km freeway with a speed limit of 80 km/h and for the scenario given in Section 4.1. A value for $\text{T}\Delta u_{\text{nominal}}$ is computed as follows: we consider a simulation where the speed limit changes with $v_{\text{step}} = 10$ km/h at every control step. So

$$\text{T}\Delta u_{\text{nominal}} = \sum\_\ell = 0^{N_{\text{c}}-1} v_{\text{step}}^2 = N_{\text{c}} v_{\text{step}}^2 \tag{9}$$

For solving the MPC optimization problem we have adopted a multi-start sequential quadratic programming (SQP) [20] optimization method. More specifically, we have used the `fmincon` command of the Matlab optimization toolbox.

4.3 Simulation results

The three performance indicators defined to analyze the simulation results are the total CO emissions, total fuel consumption, and the total time spent (TTS). The results of the simulation are shown in Table 1.

Simulation scenario	TTS (veh.h)	Total CO (kg)	Total Fuel (l)
S1	23.563	28.009	21741
S2	27.826	1.0614	1027.7
S3	14.004	20.093	16730

Table 1: Simulation results

As it can be seen from the table, the TTS, total CO, and total fuel consumed respectively are 23.563 veh·h, 28.009 kg, and 21741 l, when the system is not controlled (**S1**). When an MPC controller with an objective function of reducing total CO emission and total fuel consumption (**S2**) is used, both the total CO emission and total fuel consumption are respectively reduced by 96.21% and 95.28%. However, the TTS is increased by 18.09%. On the other hand if the controller aims on the reduction of all the performance indicators (TTS, total CO emission, and total fuel consumption) as in **S3**, we observe that all of the performance measures are reduced relative to the uncontrolled scenario. Quantitatively, the total CO emission is reduced by 23.05%, total fuel consumption is reduced by 28.26%, and total time spent is reduced by 40.57%.

Moreover, since there is proportional relationship between fuel consumption and CO_2 emission, it is also possible to deduce that the CO_2 emission is also reduced.

5 Conclusions

We have proposed a model-based traffic flow control approach to reduce total CO emissions, total fuel consumption, and total time spent. This control method uses a prediction model and on-line optimization to determine the optimal traffic control measures over a given prediction horizon, which are subsequently applied using a receding horizon approach. We have illustrated the approach using a car-following traffic flow model and a dynamic microscopic emission model. In addition we have considered a case study involving a single-lane one-way traffic freeway to show how MPC can be applied to provide a balanced trade-off between conflicting performance measures. The results of this case study also demonstrate the possible solutions MPC can offer for mobility, energy, and environmental challenges.

Based on simulation results, we have shown that the focus on the reduction of total CO emission or fuel consumption alone can have negative consequence on the traffic flow under jammed traffic conditions. The simulation results suggest that the challenge of reducing CO emissions and fuel consumption while improving the traffic can be realized by proper definition of an objective function in an MPC based traffic controller. More specifically, the simulations indicate 23.05%, 28.26%, and 40.57% reduction of CO emissions, fuel consumptions, and total travel time respectively. Moreover, by addressing fuel consumption one can also implicitly reduce the CO_2 emissions.

Acknowledgements

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