How Much does Traffic Congestion Increase Fuel Consumption and Emissions? Applying a Fuel Consumption Model to the NGSIM Trajectory Data

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Abstract

The fuel consumption of vehicular traffic (and associated CO_2 emissions) on a given road section depends strongly on the velocity profiles of the vehicles. The basis for a detailed estimation is therefore the consumption rate as a function of instantaneous velocity and acceleration. We present a model for the instantaneous fuel consumption that includes vehicle properties, engine properties, and gear-selection schemes and implement it for different passenger car types representing the vehicle fleet under consideration. We apply the model to trajectories from microscopic traffic simulation. The proposed model can directly be used in a microscopic traffic simulation software to calculate fuel consumption and derived emission such as carbon dioxide. Next to travel times, the fuel consumption is an important measure for the performance of future Intelligent Transportation Systems. Furthermore, the model is applied to real traffic situations by taking the velocity and acceleration as input from several sets of the NGSIM trajectory data. Dedicated data processing and smoothing algorithms have been applied to the NGSIM data to suppress the data noise that is multiplied by the necessary differentiations for obtaining more realistic velocity and acceleration time series. On the road sections covered by the NGSIM data, we found that traffic congestion typically lead to an increase of fuel consumption of the order of 80% while the travelling time has increased by a factor of up to 4. We conclude that the influence of congestions on fuel consumption is distinctly lower than that on travel time.

Introduction

One of the central questions in transportation science is the evaluation of environmental impacts and the external costs of vehicular traffic [1, 2, 3, 4]. Particularly, this requires a reliable estimation of the fuel consumption and associated emissions of, e.g., CO_2, hydrocarbons, or particulated matter. It is particularly relevant to which degree the fuel consumption and the emissions are influenced by the frequent occurrence of congested traffic. Since consumptions and emissions depend strongly on the velocity and acceleration patterns, a detailed microscopic estimation tool is necessary for a sufficiently realistic estimation.

In such models, the instantaneous fuel consumption is determined as a function of the actual speed, the instantaneous acceleration, and further parameters and state variables for the vehicle and the engine. Such models can be formulated in tems of nonlinear regression functions [5], or they can be based on physical principles, see, e.g., [6]. They are also contained in some traffic simulators (for example, in the commercial product VISSIM). Because the physical model has more intuitive model parameters (such as mass, size, and air-drag coefficient) and is based on generally valid principles, it is more straightforward to include new vehicle types compared to the regression models.

However, while some aspects of fuel consumption and emissions such as the required instantaneous power can formulated analytically with a good accuracy, this is not true for the complicated combustion processes and associated control algorithms of the engine itself. Consequently, the analytic physical approach has to be combined with appropriate engine characteristic maps. Such maps are obtained from dynamometer tests in form of numerical tables representing fuel efficiency or relevant emission rates as a function of the operating state of the engine (effective pressure, revolution rate, temperature and others). Finally, a model is needed to calculate the engine operating state from the output of the physical model (i.e., the required power), a gear selection model, and the velocity.

In this contribution we combine the physical model and engine characteristic maps to an estimation tool that gives the instantaneous fuel consumption as a function of the velocity, the acceleration, and the selected gear. We implement the estimation tool for two typical types of passenger cars: a compact car and medium-sized vehicle and apply it to the trajectory data of the NGSIM datasets [7]. By comparing the avarage consumption rates based on trajectories in free and congested regions of the NGSIM data, we estimate the degree to which traffic congestion increases the fuel consumption.

While there are some larger-scale investigations using real-life floating car data (FCD) [8], there is, to our knowledge, no published larger-scale application of consumption models to trajectory data. Notice that, in contrast to FCD, trajectory data comprise all vehicles in a certain spatiotemporal region. Moreover, the drivers are unaware of being observed, so their behaviour can be considered as mor representative.

Our paper is structured as follows: In the following section, the model for the instantaneous fuel consumption will be presented. In the next two sections, the model will be applied to trajectories simulated with a car-following model, and to the NGSIM data. The paper will conclude with a discussion.

Instantaneous Fuel Consumption Model

The instantaneous fuel consumption can be defined by the fuel flow $Q = \frac{\mathrm{d}C}{\mathrm{d}t}$ (consumed volume C per time unit) that is consumed by the engine of the vehicle. The fuel flow Q is a function of the velocity v, the acceleration $\dot{v}$, and the gear G: $Q = Q(v, \dot{v}, G)$. Using the chain rule, this can also be expressed in terms of the instantaneous consumption per distance, C_x by

$$C_x := \frac{\mathrm{d}C}{\mathrm{d}x} = \frac{1}{v}\frac{\mathrm{d}C}{\mathrm{d}t} = \frac{Q}{v}. \tag{1}$$

This quantity can be given, for example, in terms of liters per km, or gallons per mile. To avoid unit-specific prefactors in equations such as (1), we will stick to SI units in all equations of this section, unless stated otherwise. Furthermore, for a better readability, we have dropped the vehicle index in Eq. (1) and will do so in the rest of this section. It is, however, implicitly assumed that all variables and parameters may be different for each vehicle. The main influencing factors of the instantaneous fuel consumption are the following:

- The velocity v and acceleration $\dot{v}$ of the vehicles are provided as exogenous input variables from data or microscopic traffic simulations.
- The gear G must be given externally by a gear selection scheme. The gear may be selected manually or by automatic transmission.
- Vehicle properties such as weight, size, air-drag coefficient (cd-value), and transmission ratios have a direct impact.
- Engine properties are considered by a characteristic map for the fuel consumption.
- Furthermore, external conditions (weather, temperature, road conditions etc.), and the state of vehicle and engine (e.g., the temperature of the engine cooler) are relevant as well.

In our fuel consumption model, relevant vehicle and engine properties as well as gear-shift schemes are incorporated explicitly. Furthermore, we will consider “normal” external conditions and engines running at their designed state (particularly, not immediately after a cold start). In the following subsections, we will specify the engine properties, the car properties and the gear selection scheme.

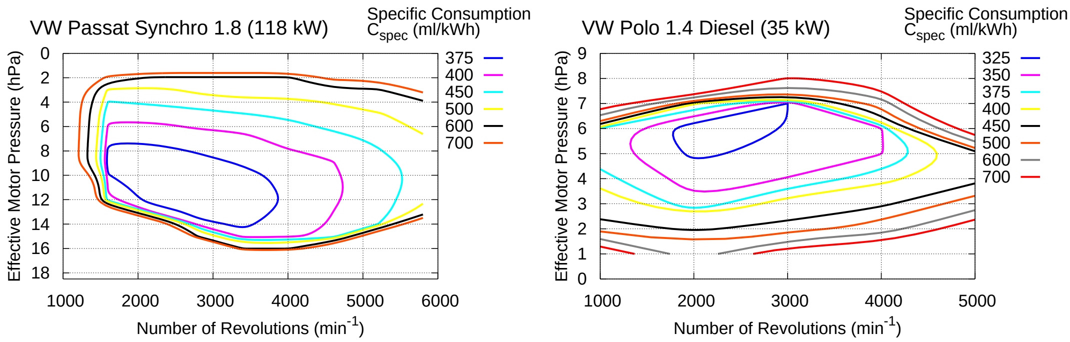

Figure 1: Engine characteristic maps for the specific fuel consumption C_{spec} of two different passenger car engines (one gasoline and one Diesel) as a function of the effective pressure p_{e} (which corresponds to the throttle position), and the revolutions f per minute.

Engine Properties

The fuel consumption depends mainly on the effective motor pressure p_{e}, and on the revolution rate f of the car crankshaft. It is given by so-called *engine characteristic maps* where the specific consumption $C_{\text{spec}}(p_{\text{e}}, f)$ (liters of fuel per kWh of mechanical work) is plotted as a function of the effective pressure p_{e} and the revolution rate f, see Fig. 1.

Using the volumetric caloric value (enthalpy) Δh_{vol} of the fuel which is 36 MJ/l or 10 kWh/l for gasoline, and 38.5 MJ/l or 10.7 kWh/l for Diesel, $C_{\text{spec}}(p_{\text{e}}, f)$ can be transformed to a map for the (unit-less) fuel energy efficiency $\gamma(p_{\text{e}}, f)$:

$$\gamma(p_{\text{e}}, f) = \frac{1}{\Delta h_{\text{vol}} C_{\text{spec}}(p_{\text{e}}, f)}. \tag{2}$$

Since the efficiency is defined by the ratio between the mechanical work W and the enthalpy $\Delta H = \Delta h_{\text{vol}} C$ of the fuel, the flow rate $Q = \frac{\text{d}C}{\text{d}t}$ can be expressed in terms of the efficiency and the mechanical power $P = \frac{\text{d}W}{\text{d}t}$,

$$Q(P, p_{\text{e}}, f) = \frac{P}{\Delta h_{\text{vol}} \gamma(p_{\text{e}}, f)}. \tag{3}$$

Finally, the effective pressure p_{e} can be expressed in terms of the mechanical power. For four-stroke engines, the relation is given by

$$p_{\text{e}} = \frac{2P}{V_{\text{cyl}} f}, \tag{4}$$

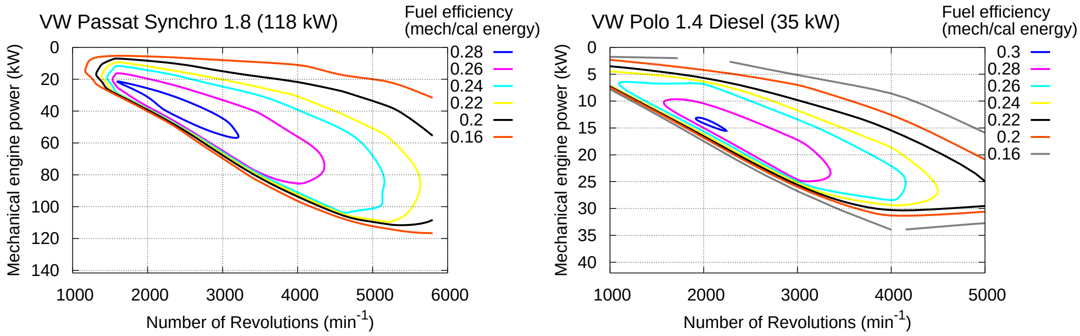

Figure 2: Examples for fuel efficiency maps $\tilde{\gamma}$ as a function of the mechanical engine power P and the revolution rate f for a gasoline and a Diesel engine.

where V_{cyl} denotes the active volume of all the cylinders of the engine. Inserting Eq. (4) into Eq. (3) yields the final expression of the fuel flow rate as a function of the power P and the revolution rate f,

$$Q(P, f) = \frac{P}{\Delta h_{\text{vol}} \tilde{\gamma}(P, f)}, \tag{5}$$

with the fuel efficiency

$$\tilde{\gamma}(P, f) = \gamma \left(\frac{2P}{V_{\text{cyl}} f}, f \right). \tag{6}$$

Figure 2 gives plots of the resulting efficiency $\tilde{\gamma}$ as a function of the mechanical power and the revolution rate. As shown in the diagrams, typical values of $\tilde{\gamma}$ for passenger cars are between 16% and 30%.

Car Properties

The relevant car properties determine how much mechanical power P is needed as a function of the velocity v and acceleration $\dot{v}$ of the vehicle. The main influencing factors are the following [9]:

- Electric consumers (e.g., lights or air conditioning) require a basis power P_0.
- The power to overcome solid-state friction and the rolling resistance of the tires. This will be described by a velocity-dependent friction coefficient $\mu(v) = \mu_0 + \mu_1 v$.
- The aerodynamic drag which leads to a force that is proportional to the velocity squared, see below.
- The power needed to overcome the inertia force when accelerating, or the gravitational drag when driving on a slope.

Parameter	VW Passat Synchro	VW Polo Diesel
Effective cylinder volume C_{cyl}	1.8 l	1.4 l
Basic power consumption P_0	3 kW	2 kW
Vehicle mass m	1600 kg	1050 kg
Friction coefficient μ_0	0.015	0.015
Friction coefficient μ_1	0.0003 s/m	0.0003 s/m
Cross-sectional area A	2.03 m^2	1.70 m^2
Air-drag coefficient (cd-value) c_w	0.32	0.36

Table 1: Car data for typical passenger cars like a VW Passat and a VW Polo.

Putting all terms together and taking into account that the power P to overcome forces is given by the velocity times this force, this leads to

$$\tilde{P}(v,\dot{v}) = P_0 + v\left[m\left\{\dot{v} + (\mu_0 + \mu_1 v + \beta)g\right\} + \frac{1}{2}c_w\rho A v^2\right], \tag{7}$$

where $g = 9.81\,\mathrm{m/s^2}$ is the gravitational constant, $\rho = 1.2\,\mathrm{kg/m^3}$ is the density of air (near sea level), and β is the slope of the road (positive, when uphill). Additionally, expression (7) includes several vehicle properties that are summarized in Table 1 for typical passenger cars.

Equation (7) gives the required power as a function of velocity and acceleration in all driving situations where this expression yields a positive value. For negative values of $\tilde{P}$ corresponding to braking and/or downhill situations, the consequences for the fuel consumption depend on the motor management and the driving style:

- The driver brakes without using the motor brake. Then, P is equivalent to the idling power that is of the order of P_0.
- The motor brake is used. Then, in sufficiently modern vehicles, the throttle cutoff is activated and the consumption, i.e., the required engine power, drops to zero.
- Hybrid vehicles can use the kinetic energy to charge the batteries, i.e, the effective power is negative and (assuming no losses) given directly by Eq. (7).

Here, we will use the most realistic "throttle-cutoff" scenario, where the power relevant for the fuel consumption is given by

$$P(v,\dot{v}) = \max\left(\tilde{P}(v,\dot{v}), 0\right). \tag{8}$$

Gear selection scheme

The Eq. (5) together with Eq. (8) gives the consumption rate as a function of v, $\dot{v}$, and f. In order to eliminate the crankshaft revolution rate f, it will be mapped to the velocity and the gear G using the gearbox transmission ratios ϕ_G and the dynamic tire radius r_{dyn} of the vehicle,

$$f(v, G) = \frac{v}{2\pi r_{\text{dyn}} \phi_G}. \tag{9}$$

With Eqs. (9) and (8), the consumption rate (5) can be expressed in terms of v, $\dot{v}$, and G. Finally, the gear is determined as a function of velocity and required acceleration by the "fuel-optimal" scheme:

$$G = G(v, \dot{v}) = \underset{G'}{\operatorname{argmin}} \left[Q(v, \dot{v}, G') \right]. \tag{10}$$

Figure 3 shows the resulting instantaneous consumption per distance

$$C_x(v, \dot{v}) = Q(v, \dot{v})/v, \tag{11}$$

which is given by inserting Eqs. (5)–(10) into Eq. (1) for a gasoline and a Diesel-driven car, respectively. Furthermore, the optimal gear has been displayed. The results are plausible. Particularly, a lower gear is selected if a higher acceleration is required ("kick-down"). Furthermore, the Diesel-driven car generally has a lower consumption, particularly at lower velocities.

For matters of illustration, Fig. 4 shows the instantaneous consumption C_x and the associated optimal gear for a constant acceleration $\dot{v} = 0$ derived from the two-dimensional contour plots 3. As an interesting result, one directly gets the maximum velocity of the two considered passenger cars. The strong engine of the VW Passat 1.8 has a maximum velocity of about 200 km/h while the Polo 1.4 Diesel engine with an engine power of just 35 kW only reaches a maximum velocity of about 145 km/h. Furthermore, the depicted values of $C_x(v)$ are plausible and may be considered as a first consistency check of the model.

Application to Simulated Trajectories

For matters of illustration, we will now apply the instantaneous fuel flow $Q(t) = Q(v(t), \dot{v}(t))$ together with the optimal gear-shifting scheme (10) to a vehicle trajectory. As exogenous input variables we have to provide the instantaneous velocity $v(t)$ and acceleration $\dot{v}(t)$ which we have generated by using the "Intelligent Driver Model" [10] which is a common car-following model. For details on the model, we refer to the website `www.traffic-simulation.de` which provides a description of the model and an open-source implementation of an associated simulation framework. Figure 5 (top

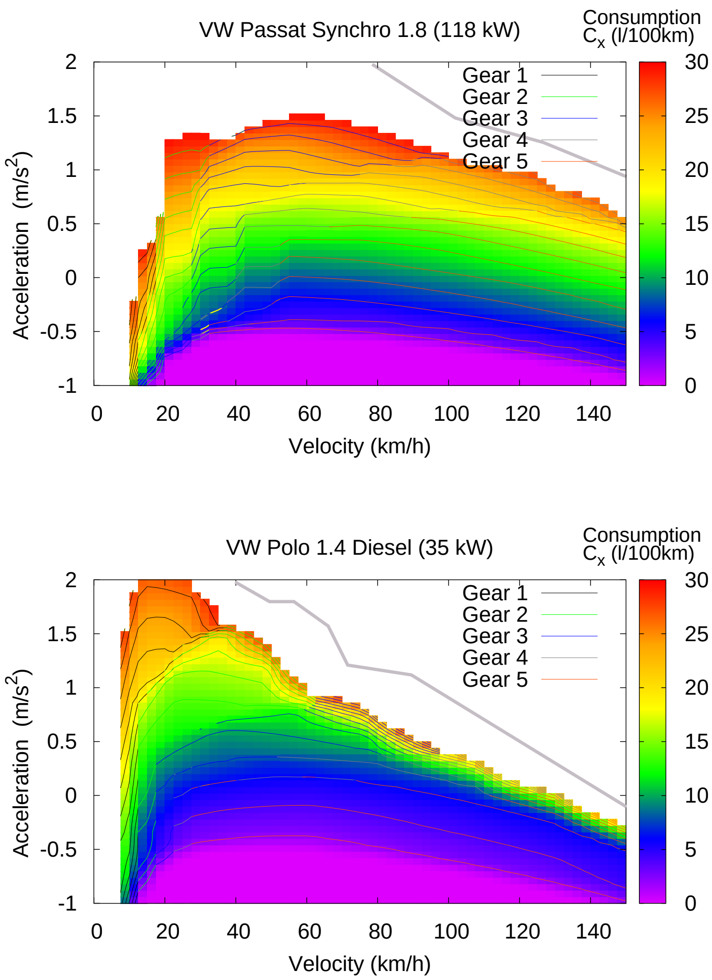

Figure 3: Instantaneous consumption C_x (in liters per 100 km) and selected gears of two car types as a function of the velocity and acceleration when driving according to the fuel-optimal gear-selection scheme. In the range of velocity and acceleration where $C_x = 0$ the driver brakes in addition to the motor brake. In the white region below the gray line, the instantaneous consumption exceeds 30 liters per 100 km. The white region above the gray line is not accessible because the motor power is not sufficient. The maximum velocity of the respective car is given by the velocity value where this "forbidden" region intersects with the line of zero acceleration $\dot{v} = 0$.

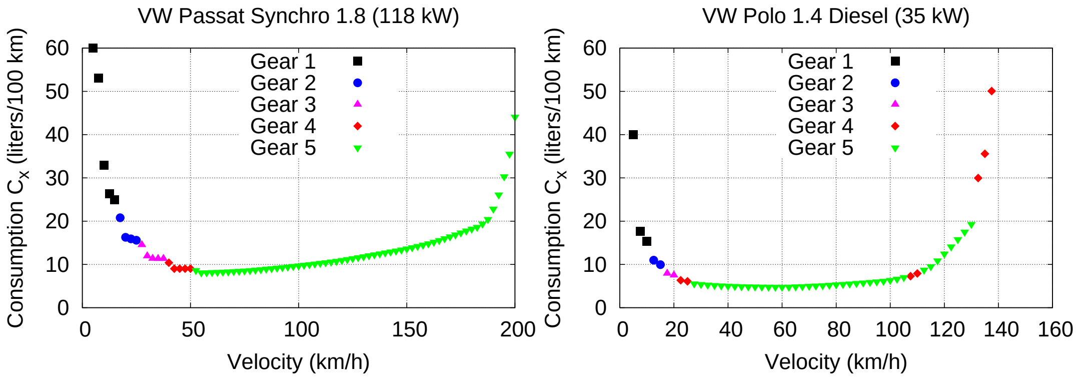

Figure 4: Instantaneous consumption C_x (in liters per 100 km) and associated optimal gear for constant acceleration $\dot{v} = 0$. Notice that near the maximum velocity, the forth gear has to be taken since the fifth gear is a dedicated "fuel-saving" gear.

row) shows the considered traffic situation by means of the velocity and acceleration profile. The scenario consists of an acceleration period from a standstill to the free speed of 100 km/h and a deceleration period due to approaching a standing obstacle which is originally located 4200 m ahead. For matters of comparison, we consider two different settings of the model parameter a which determines the maximum acceleration: $a = 0.5\,\mathrm{m/s^2}$ (scenario 1) and $a = 1.2\,\mathrm{m/s^2}$ (scenario 2).

The bottom row of Fig. 5 shows the resulting instantaneous fuel flow $Q(t)$ as calculated by Eq. (5) for the medium-sized car "VW Passat Synchro 1.8" and the compact car "VW Polo Diesel 1.4". We observe the following:

- Generally, the higher motorized vehicle type shows a higher fuel consumption than the compact car for the same driving maneuver.
- In the acceleration period of Scenario 2, the compact car displays a higher consumption rate. This is due to the fact that the engine is at the limit of its power for this vehicle and this driving situation resulting in a less efficient combustion regime.
- During the braking period, the fuel consumption is zero due to the considered throttle cutoff.
- The gear-switching operations of the Passat model become obvious during the acceleration period leading to spikes in the consumption curve while no such spikes are seen in the smaller car.

Having calculated the instantaneous fuel flow $Q(t)$, we can easily derive the *total fuel*

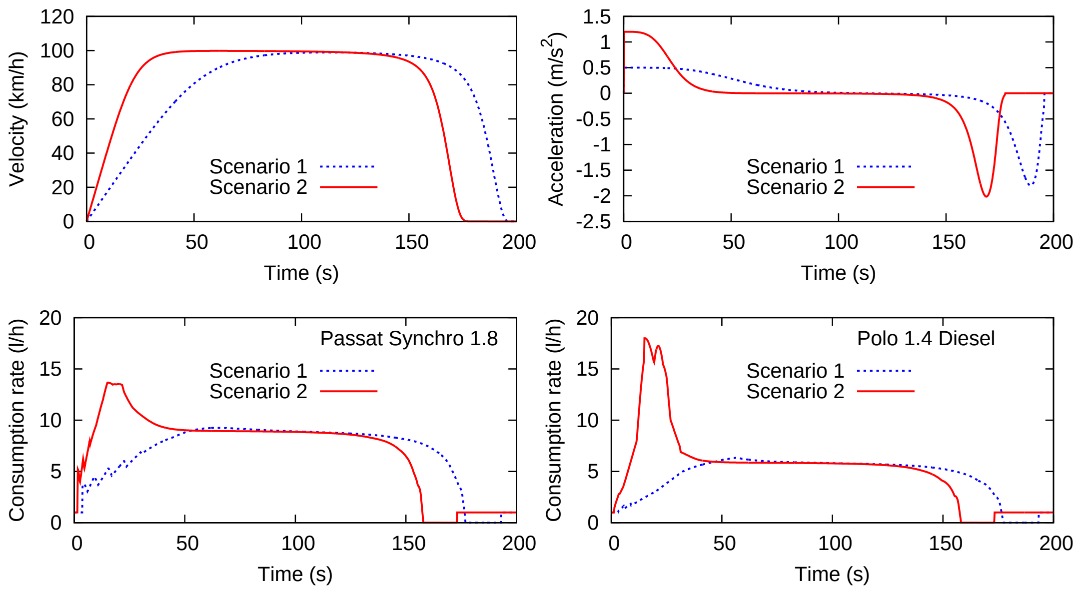

Figure 5: Application of the fuel consumption model to simulated vehicle trajectories using the "Intelligent Driver Model" as microscopic traffic model. The top row shows the velocities and accelerations for following driving maneuver: Acceleration to the desired velocity of 100 km/h, a free driving period and a braking period while approaching a standing obstacle. Scenario 1 shows the profile of a low maximum acceleration parameter $a = 0.5\,\mathrm{m/s^2}$ while scenario 2 corresponds to a higher value $a = 1.2\,\mathrm{m/s^2}$. The bottom row shows the resulting instantaneous consumption rates according to (5) for two types of passenger cars. The spikes in the fuel consumption profile of the Passat are caused by gear-shifting.

consumption of a given trajectory by integrating over the time period $[t_{\text{start}}, t_{\text{end}}]$:

$$C = \int\limits_{t_{\text{start}}}^{t_{\text{end}}} Q\big(v(t), \dot{v}(t)\big)\ \mathrm{d}t. \tag{12}$$

For the traffic scenario 1 showed in Fig. 5, we get a total consumption of 0.492 l (scenario 2: 0.531 l) for the medium-sized car type and 0.319 l for the compact car. In most cases it is more intuitive to refer to the fuel consumption per distance, C_x. Here, the distance has been 4.19 km. Thus, we obtain an average fuel consumption for the scenario 1 of 11.7 l/100km (scenario 2: 12.7 l/100km) for the Passat and 7.6 l/100km for the Polo. These findings are of the expected (realistic) magnitude.

Application to Empirical Trajectory Data

Let us finally apply the presented fuel consumption model to empirical trajectory data to calculate the total fuel consumption of a set of passenger cars. For this study, we use trajectory data that have been collected at the Berkeley Highway Laboratory (BHL) in Emeryville, California, by Cambridge Systematics, Inc. and the California Center for Innovative Transportation at the University of California in Berkeley in the framework of the Next Generation SIMulation (NGSIM) project of the Federal Highway Administration of the U.S. Department of Transportation [7]. As part of the California Partners for Advanced Highways and Transit (PATH) Program, the Institute of Transportation Studies at UC Berkeley further enhanced the data collection procedure [11]. We will use the following three data sets that are freely available for download on the NGSIM homepage (`www.ngsim.fhwa.dot.gov`): (i) The "Prototype Dataset" covers a road section of approximately 900 m length in a 30-minute period recorded in December 2003. To this end, six cameras have been mounted on top of the 97 m tall Pacific Park Plaza tower and recorded 4733 vehicles. (ii) As part of the California Partners for Advanced Highways and Transit (PATH) Program, the Institute of Transportation Studies at UC Berkeley further enhanced the data collection procedure [11]. In April 2005, another trajectory dataset was recorded at the same location using seven cameras and capturing a total of 5648 vehicle trajectories in three 15-minute intervals on a road section of approximately 500 m. This dataset was later published as the "I-80 Dataset". (iii) In June 2005, another data collection has been made using eight cameras on top of the 154 m tall 10 Universal City Plaza next to the Hollywood Freeway US-101. On a road section of 640 m, 6101 vehicle trajectories have been recorded in three consecutive 15-minute intervals. This dataset has been published as the "US-101 Dataset". The Prototype Dataset contains free and bound traffic while the data of the other sets mostly contains congested traffic.

Data Preparation: Trajectory Smoothing

The trajectory data sets seem to be unfiltered and exhibits some noise artefacts. For example, in the Prototype dataset two thirds of all accelerations as derived quantities are beyond $\pm 3\,\mathrm{m/s}^2$. As the fuel consumption is sensitive to velocity or acceleration noise, we first have to deal with the smoothing of the trajectories. A first check using the noisy data showed unrealistically high values for the fuel consumption C_x of the order of 1000 l/100km. Therefore, we use a method based on a *symmetric exponential moving average filter (sEMA)* which is shortly described in this section. For a more detailed presentation and analysis of this tool we refer to Ref. [12].

Let $x_\alpha(t_i)$ denote the measured position of vehicle α at time t_i, where $i = 1 \ldots N_\alpha$ and N_α denotes the number of datapoints of the trajectory. The smoothing kernel is given by $g(t) = \exp(-|t|/T)$ where T is the smoothing width. Since the datapoints are equidistant in time with interval dt, we can formulate the smoothing operation by using datapoint indices instead of times. The smoothed positions $\tilde{x}(t_i)$ are given by

$$\tilde{x}_\alpha(t_i) = \frac{1}{Z} \sum_{k=i-D}^{i+D} x_\alpha(t_k)\, e^{-|i-k|/\Delta} \quad \text{where } Z = \sum_{k=i-D}^{i+D} e^{-|i-k|/\Delta}. \tag{13}$$

The width Δ is given by T/dt. The smoothing window width $D = \max\{3\,\Delta, i-1, N_\alpha - i\}$ is chosen to be three times the smoothing kernel width for any data point that is not closer than D data points to either trajectory boundary. For the points near the boundaries, the smoothing width is decreased to ensure that the smoothing width is always symmetric.

Next to the smoothing procedure, we have to define the order of differentiations and smoothing operations. Here, we first differentiate to velocities and accelerations and then we apply the smoothing to the three variables of positions, velocities and accelerations. This order turned out to better reproduce artificial benchmark trajectories [12]. Finally, we have to define the smoothing widths T for each quantity. Here, we have used $T_x = 0.5\,\text{s}$ for the positions, $T_v = 1\,\text{s}$ for the velocities and $T_a = 4\,\text{s}$ for the acceleration.

Fuel Consumption in Free and Congested Traffic

For calculating the total fuel consumption of a set of vehicles, we have to sum Eq. (12) over all vehicle trajectories $\alpha = 1 \ldots N$:

$$C_\text{tot} = \sum_\alpha \int_{t^\alpha_\text{start}}^{t^\alpha_\text{end}} Q_\alpha\big(v_\alpha(t), \dot{v}_\alpha(t)\big)\ \text{d}t. \tag{14}$$

Together with the total distance L_tot of the vehicle set given by

$$L_\text{tot} = \sum_\alpha \left(x^\alpha_\text{end} - x^\alpha_\text{start}\right), \tag{15}$$

the average fuel consumption per distance, $\langle C \rangle_x$ is then given by

$$\langle C \rangle_x = \frac{C_\text{tot}}{L_\text{tot}}. \tag{16}$$

For our set of trajectories, we have filtered the NGSIM datasets for passenger cars with a time series duration of at least 10 s. Furthermore, we have restricted our set to trajectories of the four inner lanes in order to exclude merging vehicles. In total, we have considered a set of 9169 trajectories with a total length of 5166 km. The average travel time has been determined to 2.82 h/100km corresponding to an average velocity

Traffic Regime:	Total	Free	Bound	Cong.
Number of Trajectories	9169	1818	1933	8277
Total Length (km)	5166	1008	563.9	3456
Total Duration (h)	145.6	9.71	8.36	135
Avg. Travel Time (h/100km)	2.82	0.963	1.482	3.92
Avg. Velocity (km/h)	35.5	103.9	67.5	25.5
Fuel Consumption C_{tot} (liters)	608.4	83.1	35.6	509
Fuel Consumption $\langle C \rangle_x$ (l/100km)	11.8	8.24	6.30	14.7

Table 2: Results for the NGSIM trajectory data filtered for passenger cars and, additionally, for traffic regimes. The "free traffic" regime includes trajectories with velocities above 90 km/h while velocities below 54 km/h have been attributed to "congested traffic". The intermediate regime characterizes "bound traffic". The total fuel consumption has been calculated for the "VW Passat Synchro" model representing a typical medium-sized vehicle.

of 35.5 km/h. By applying our fuel consumption model with the Passat Synchro as considered vehicle type, we have obtained a total fuel consumption of 608.4 liters which (according to Eq.(16)) corresponds to an average fuel consumption of $\langle C \rangle_x = 11.8\,\text{l}/100\text{km}$. The results of our data filtering and analysis process are listed in Table 2.

Furthermore, we have filtered the trajectories additionally with respect to traffic conditions: Trajectories with all their velocities above $v_{\text{free}} = 90\,\text{km/h}$ have been attributed to "free traffic", while velocity profiles below $v_{\text{cong}} = 54\,\text{km/h}$ have been associated with "congested traffic". The intermediate regime characterizes "bound traffic". If a trajectory exhibits a velocity profile that corresponds to multiple regimes, it was split into the largest possible pieces that are at least 10s long and lie in one regime only. The obtained average travel times and the total fuel consumptions for the three traffic regimes are summarized in Table 2.

As main result we have calculated the average fuel consumption $\langle C \rangle_x$ for the three traffic regimes: The fuel consumption in congested traffic is 14.7 l/100km and therefore increased by about 80% compared to free traffic conditions resulting in 8.24 l/100km. The intermediate regime shows the lowest fuel consumption corresponding to the global minimum in the consumption rate for velocities between 50 and 80 km/h depicted in Fig. 4. In contrast, the average travel time has been increased by a factor of about 4 due to traffic congestion. We therefore conclude that the impact of traffic congestion on fuel consumption is distinctly lower than that on travel time.

Finally, a discussion of the dependency of the findings on the applied trajectory smoothing is in order. We checked the results for different smoothing widths T_a and found only a weak influence on the resulting total fuel consumptions: Applying a lower smoothing width $T_a = 2\,\text{s}$ to the free traffic regime leads to $\langle C \rangle_x^{\text{free}} = 9.27\,\text{l}/100\text{km}$ while an increased smoothing parameter $T_a = 8\,\mathrm{s}$ results in $\langle C\rangle_x^{\text{free}} = 7.98\,\mathrm{l}/100\mathrm{km}$. This variation below 20% is negligible compared to the results for the unsmoothed trajectory data which lead to arbitrarily high fuel consumptions. This observation is not an error of the proposed fuel consumption model but a consequence of the applied numerical penalty because the noise in the accelerations directs to physically not accessible regimes in the state space of $C_x(v, \dot{v})$ (see Fig. 3). Therefore, the fuel consumption model can be seen as a consistency check for the realism of the applied data.

Discussion and Conclusions

Next to travel time, the fuel consumption and the associated emissions of CO_2, hydrocarbons, or particulated matter, are essential factors when estimating the societal costs associated with vehicular traffic.

On the most macroscopic level, fuel consumptions are usually determined by multiplying the average consumption of a representative vehicle fleet (per kilometer or per mile) with the estimated overall traffic performance in a certain time period (vehicle-kilometers or vehicle-miles). For determining the influence of traffic congestions on the consumption and emissions, however, this method is not sufficient because the fuel consumption depends strongly on the velocity profile.

In this contribution, we have therefore proposed a more microscopic approach based on the instantaneous fuel consumption in terms of liters per km or per time unit as a function of velocity and acceleration of the corresponding vehicle. Besides vehicle-related properties such as the mass, the cd value or gearbox transmission ratios that can be easily obtained for a representative vehicle fleet, the method needs as input engine characteristic engine maps for the fuel consumption rate), and a gear-switching scheme. Since CO_2 is directly linked to the fuel consumption (2.40 kg/l for gas [ROZ 95] and 2.68 kg/l for Diesel fuel) it can be calculated as well. In order to calculate other emissions such as NOx or particulate matter, the corresponding characteristic engine emission map is needed which will be used instead of the consumption characteristic map. For reasons of confidentiality, however, such characteristic maps often are difficult to obtain for the most recent generation of vehicles and engines. The characteristic maps used for this work come from engines for a compact car type and a medium-sized vehicle type that has been sold for more than ten years. This does not necessarily restrict the relevance of the results since such vehicles types are very common in the present vehicle fleet. Nevertheless, the two vehicle types cannot be considered as representative for the whole vehicle fleet and the present study should be considered as a *proof of concept*.

There are several applications: In the context of microscopic traffic *simulation* and simulation-based optimization, the fuel and emission model can be used to include such parts to the objective function and to calculate the corresponding contributions. This is relevant, e.g., for optimizing traffic-control schemes, or measuring the performance of

Intelligent Transportation Systems (ITS) [13].

Furthermore, the present work is focused on another application: A more detailed estimation of the influence of traffic congestion on fuel consumption and emissions that has become possible by the availability of the NGSIM datasets. We have obtained the remarkable result that traffic congestions that have increased the travel time by a factor of four only led to an increase of the fuel consumption by a factor of less than two. Moreover, the average fuel consumption for "bound" traffic, i.e., a situation where traffic is neither completely free or congested, is even less than in free traffic.

Finally, the instantaneous fuel consumption as proposed in this work is very sensitive with respect to the acceleration profile. For example, even comparatively small amounts of acceleration noise will lead to significantly higher consumption levels. This can be used as a sensitive test to check whether a certain model or traffic simulator produces realistic velocity and acceleration patterns, or whether the measurement noise in trajectory data (such as the NGSIM data) has been eliminated sufficiently .

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