A Statistical Model of Vehicle Emissions and Fuel Consumption

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***Abstract*—Many vehicle emission models are overly simple, such as the speed dependent models used widely, and other models are sufficiently complicated as to require excessive inputs and calculations, which can slow down computational time. We develop and implement an instantaneous statistical model of emissions (CO_2, CO, HC, and NOx) and fuel consumption for light-duty vehicles, which is simplified from the physical load-based approaches that are gaining in popularity. The model is calibrated for a set of vehicles driven on standard as well as aggressive driving cycles. The model is validated on another driving cycle in order to test its estimation capabilities. The preliminary results indicate that the model gives reasonable results compared to actual measurements as well as to results obtained with CMEM, a well-known load-based emission model. Furthermore, the results indicate that the model runs fast and is relatively simple to calibrate. The model presented can be integrated with a variety of traffic models to predict the spatial and temporal distribution of traffic emissions and assess the impact of ITS traffic management strategies on travel times, emissions, and fuel consumption.**

***Index Terms*—Instantaneous emissions modeling, integration of dynamic traffic and emission models, vehicle emissions and fuel consumption.**

I. INTRODUCTION

INTELLIGENT Transportation Systems (ITS) have many potential societal benefits ranging from congestion relief to reduction of energy consumption and air quality control. Vehicle emission models are necessary for quantifying the impact of traffic flows on air quality.

It has been widely recognized that models based on the average speed from fixed driving cycles, such as the US EPA MOBILE6, do not adequately capture the effects of driving and vehicle dynamics on emissions [1]. Therefore their applicability is limited to the estimation and forecast of large-scale emissions inventories.

In order to predict traffic emissions more accurately and with a higher spatial and temporal detail, instantaneous or modal emission models are necessary. They are based respectively on instantaneous vehicle kinematic variables, such as speed and acceleration, or on more aggregated modal variables, such as time spent in acceleration mode and time spent in cruise mode. These models can be classified into emission maps (speed/acceleration lookup tables), purely statistical models, and load-based models.

Although easy to generate and use, emission maps are not satisfactory because they can be highly sensitive to the driving cycle that was used to calibrate them. They are also sparse and not flexible enough to account for such factors as road grade, accessory use, or history effects. Properties and limitations of emission maps are discussed in more detail in [2].

Purely statistical models typically consist of linear regressions that employ functions of instantaneous vehicle speed and acceleration as explanatory variables. These models can lack a clear physical interpretation and can also overfit the calibration data due to a large number of explanatory variables. There is work in the literature which uses this approach [3], [4].

Load-based models simulate, through a series of modules, the physical phenomena that generate emissions. The primary variable of these models is the fuel consumption rate, which is a surrogate for engine power demand (or engine load). They have a detailed and flexible physical basis, which defines the variables and parameters that should be included when modeling emissions. On the other hand, these models are quite complex and, when applied to the entire flow of vehicles in a network over a period of time, the computational effort can be high. Ultimately, they too can be sensitive to the calibration data, though they are more robust as a result of their physical basis.

It is valuable to design a model that simultaneously obtains realistic results, is fast to run, and is easy to calibrate in different situations. This paper presents EMIT (EMIssions from Traffic), a simple statistical model for instantaneous emissions (CO_2, CO, HC, and NO_x) and fuel consumption. In order to realistically capture the emissions behavior, the explanatory variables have been derived from a load-based

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approach. The model, due to its simple structure, is relatively easy to calibrate and requires less computational time.

The paper is organized as follows. Section II presents the structure of the model. Section III describes the data used to calibrate and validate the model. Sections IV and V analyze respectively the results of calibration and validation. Section VI provides conclusions and directions for future work.

II. Model structure

EMIT is composed of two modules, as shown in Fig.1: the engine-out emissions module and the tailpipe emissions module. Although modeling two modules adds a level of complexity, it is interesting to predict not only tailpipe, but also its precursor, engine-out emissions. This allows for the modeling of engine and catalyst technology improvements and vehicle degradation, as well as for the quantitative assessment of the effectiveness of inspection and maintenance programs.

Given the vehicle category and its second-by-second speed and acceleration, the first module predicts the corresponding second-by-second fuel consumption rate and engine-out emissions, which are the input of the second module that predicts second-by-second tailpipe emissions.

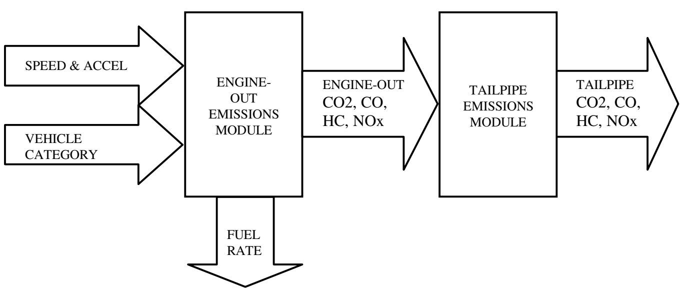

Fig. 1. Model structure.

In order to define the variables and relationships used in our model, we employ a load-based formalism. The reader interested in a more comprehensive description of the physical and chemical phenomena that generate emissions is referred to [5] and [6].

A. Engine-out emissions module

Let i denote a generic emission species (i.e. $i = CO_2, CO, HC, NO_x$). Let EO_i denote the engine-out emission rate of species i in g/s, and EI_i the emissions index for species i, which is the mass of emissions per mass unit of fuel. By definition of EI_i, engine-out emissions are given by:

$$EO_i = EI_i \cdot FR \tag{1}$$

where FR denotes the fuel consumption rate (g/s).

In a typical load-based formulation, fuel rate is modeled as:

$$FR = \begin{cases} \phi \cdot \left(K \cdot N \cdot V + \dfrac{P}{\eta} \right) & if\ P > 0 \\ K_{idle} \cdot N_{idle} \cdot V & if\ P = 0 \end{cases} \tag{2}$$

where:

ϕ: fuel/air equivalence ratio, which is the ratio of stoichiometric air/fuel mass ratio (~14.5) to the actual air/fuel ratio,

K : engine friction factor (kJ/rev/liter),

N : engine speed (rev/s),

V : engine displacement (liters),

η : engine indicated efficiency,

K_{idle} : constant idle engine friction factor (kJ/rev/liter),

N_{idle} : constant idle engine speed (rev/s), and

P : engine power output (kW).

When the engine power is zero, the fuel rate is equal to a typically small constant value. Otherwise, fuel consumption is mainly dependent on engine speed and demanded power.

The stoichiometric ratio corresponds to the mass of air needed to ideally oxidize a mass of fuel completely. Under higher power conditions, engines are typically designed to operate with a mixture rich in fuel ($\phi > 1$) in order to prevent the catalyst from overheating. This can have a significant effect on emissions, as discussed later. Enrichment also often occurs during cold-starts to heat faster the engine and exhaust so that the catalyst can light-off sooner. During long deceleration events, the mixture can go lean ($\phi < 1$) because engines are often designed to shut off the fuel since power is not required. Though less significant than enrichment, enleanment conditions can also affect emissions [7], as discussed later in this section.

The engine power is modeled as:

$$P = \frac{P_{tract}}{\varepsilon} + P_{acc} \tag{3}$$

where:

P_{tract} : total tractive power requirement at the wheels (kW),

ε : vehicle drivetrain efficiency, and

P_{acc} : engine power requirement for accessories, such as air conditioning.

The quantities K, N and ε depend on vehicle speed (and on other quantities), as discussed in [5].

Positive tractive power is given by:

$$P_{tract} = A \cdot v + B \cdot v^2 + C \cdot v^3 + M \cdot a \cdot v + M \cdot g \cdot \sin\vartheta \cdot v \tag{4}$$

where:

v : vehicle speed (m/s),

a : vehicle acceleration (m/s^2),

A : rolling resistance term (kW/m/s),

B : speed-correction to rolling resistance term (kW/(m/s)^2),

C : air drag resistance term (kW/(m/s)^3),

M : vehicle mass (kg),

g : gravitational constant (9.81 m/s^2), and

ϑ : road grade (degrees).

When the right hand side of (4) is non-positive, P_{tract} is set equal to zero. All parameters (A, B, C, and M) are known and readily available for each vehicle.

Emission indices EI_i are modeled in the literature in various ways as a function of ϕ (see [5] and [6]) or ϕ and FR (see [8]). However, generally, as more fuel is burned, more emissions are formed; thus to first approximation EO_i is a linear function of FR:

$$EO_i = \lambda + \mu \cdot FR \tag{5}$$

In particular, every emission species has a particular behavior, which is summarized as follows:

- CO_2 is the principal product of complete fuel combustion; thus, it increases linearly with FR.
- CO is sensitive to ϕ. Under enrichment conditions, the combustion is not complete due to the lack of oxygen. Much of the carbon present in the excess fuel is partially oxidized to CO instead of CO_2. Note that CO is generated even under stoichiometric conditions, due to possible partial oxidation of HC.
- HC is a product of incomplete combustion and is also usually proportional to FR. Under enleanment conditions, HC emissions can be higher, in particular during long deceleration events [7]. During decelerations, the dramatic drop in fuel results in a cessation of combustion, and hence virtually all of the remaining fuel (what little is left) is emitted unburned. However this fuel excess is typically oxidized in the catalyst. This is an example where history effects can be significant.
- NO_x is mainly dependent on the combustion temperature, because the dissociation and subsequent recombination of atmospheric N_2 and O_2 that generate NO and NO_2 is induced by high temperatures [9]. For small values of FR, very little NO_x is emitted. During stoichiometric conditions, the combustion temperature, and consequently the emission, increase as fuel is burned at a higher rate.

Fig. 2 shows the trends of engine-out emission rates versus fuel rate for the data considered in this study (see Section IV). Fuel rate is estimated using the carbon balance formula: $FR = [CO_2/44 + CO/28] \cdot [12 + 1 \cdot 1.85] + HC$, where 44, 28, 12 and 1 are the molecular weights of CO_2, CO, C, and H respectively, 1.85 is the approximate number of moles of hydrogen per mole of carbon in the fuel, and CO_2, CO, and HC are the measured engine-out emission rates [8].

With the exception of CO, the trends of the emission rate as a function of FR are approximately linear, though sometimes somewhat scattered. CO presents a linear trend for low to medium values of FR, and increases more rapidly for larger values of FR corresponding to the enrichment conditions.

EMIT is developed and calibrated for conditions of zero road grade ($\vartheta = 0$) and without accessory usage ($P_{acc} = 0$). Also, the model does not represent history effects, including cold-start and HC enleanment puffs. These factors would be included in future developments of the model. Nevertheless, considering only hot-stabilized conditions is not a critical limitation for highway applications since most vehicles are hot by the time they reach the highways. Moreover, the HC puffs do not affect significantly tailpipe emissions in normal emitting vehicles, since in enleanment conditions the catalytic converter is usually effective [7].

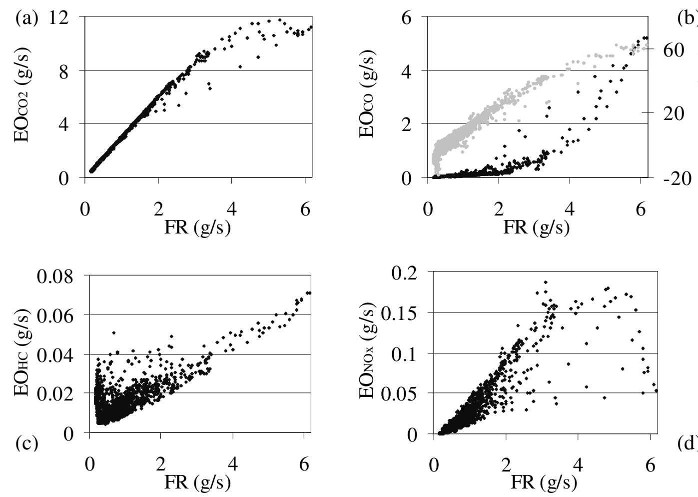

Fig. 2 – Engine-out emission rates versus fuel rate. Plot (b), in addition to engine-out CO rates, represents also tractive power versus fuel rate (in gray).

EMIT employs the following assumptions:

- The effects on fuel rate of K, N, ε and ϕ can be aggregated into the effects of v, v^2, v^3, and $v \cdot a$, which are the independent variables in (4).
- Since there is a direct correlation between fuel rate and emissions, we assume that the variables that govern emissions are the same variables that govern fuel rate.
- Since in this study we do not consider accessory usage ($P_{acc} = 0$), we use P_{tract} as a surrogate for P to test if the vehicle is in idle mode.

Based on these assumptions, combining equations (2), (3), and (4), FR can be expressed as follows:

$$FR = \begin{cases} \alpha_{FR} + \beta_{FR} v + \gamma_{FR} v^2 + \delta_{FR} v^3 + \zeta_{FR} av, & \\ \qquad\qquad if \quad P_{tract} > 0 & \text{(6a)} \\ \alpha'_{FR}, \qquad if \quad P_{tract} = 0 & \text{(6b)} \end{cases}$$

From (5) and (6), EO_i can be expressed as follows:

$$EO_i = \begin{cases} \alpha_i + \beta_i v + \gamma_i v^2 + \delta_i v^3 + \zeta_i av, & if \quad P_{tract} > 0 \quad \text{(7a)} \\ \alpha'_i, & if \quad P_{tract} = 0 \quad \text{(7b)} \end{cases}$$

where tractive power is calculated using (4).

Equations (6a), (6b), (7a), and (7b) are calibrated using ordinary least square linear regressions. The load-based model of engine-out emissions involves a multi-step calibration process of many (~20) parameters, and the prior knowledge of several publicly available specific vehicle parameters [5]. Instead, the approach proposed here collapses the calibration into just one or two linear regressions for each pollutant. This has advantages and disadvantages. First, the calibration is simpler and less time consuming, mainly due to the bypassing of the transmission (engine speed) model. More importantly, compared to a multi-step calibration, here the parameters directly optimize the fit to engine out emissions, avoiding error accumulations. Moreover, while for particular applications it is useful to have a complex and disaggregate emission model, for many transportation applications, this is not always necessary. On the other hand, the model does not take into account explicitly some variables that may affect the emissions significantly. In particular, while road grade and accessory use can be easily introduced in the estimation of P_{tract} and P in (4) and (3) respectively, it is not trivial to incorporate such variables into our more aggregated model. This issue would be addressed in future research.

B. *Tailpipe emissions module*

Tailpipe emission rates TP_i (g/s) are modeled as the fraction of the engine-out emission rates that leave the catalytic converter:

$$TP_i = EO_i \cdot CPF_i \tag{8}$$

where CPF_i denotes the catalyst pass fraction for species i.

Catalyst efficiency is difficult to predict accurately, and varies greatly from hot-stabilized to cold-start conditions. In order to model cold-start or intermediate soak catalyst efficiencies, it would be necessary to take into consideration history effects, such as soak time, time elapsed since the beginning of the trip, and possibly cumulative fuel consumption. As mentioned, at this time cold-start conditions are not considered in the model of this paper.

Hot-stabilized catalyst pass fractions are modeled in the literature in various ways as a function of ϕ, FR, and/or engine-out emissions [5], [8]. Since the physical and chemical phenomena that control catalyst efficiency are challenging to capture, often these functions are purely empirical.

EMIT calculates tailpipe emissions as follows:

- Tailpipe CO_2, which is not much different from engine-out CO_2, is modeled as:

$$TP_{CO_2} = \begin{cases} \alpha_{CO_2} + \beta_{CO_2} v + \delta_{CO_2} v^3 + \zeta_{CO_2} av, & \\ \qquad\qquad\qquad if \quad P_{tract} > 0 & (9a) \\ \alpha'_{CO_2}, \qquad\qquad if \quad P_{tract} = 0 & (9b) \end{cases}$$

- Catalyst pass fraction for CO, HC and NO_x are modeled empirically as piecewise linear functions of engine-out emission rates.

III. Data

The database used in this study is the National Cooperative Highway Research Program (NCHRP) vehicle emissions database, developed by the University of California at Riverside [5]. It includes dynamometer measurements of second-by-second vehicle speed, engine-out and tailpipe emission rates of CO_2, CO, HC, and NO_x for three driving cycles: the Federal Test Procedure (FTP) cycle, the high-speed aggressive US06 cycle, and a cycle developed at the University of California at Riverside, called Modal Emission Cycle (MEC01). The chassis dynamometer tests were conducted on more than 300 automobiles and trucks.

The primary objective of EMIT is to predict emissions from average vehicles representative of a given vehicle category, rather than from specific makes and models. Thus, a compositing procedure similar to that used in [5] has been implemented. The same 26 vehicle/technology categories defined in [5] have been adopted, with minor modifications. The categories are defined in terms of fuel and emission control technology, accumulated mileage, power-to-weight ratio, emission certification level, and finally by normal or high emitter. The compositing procedure was conducted as follows. For each vehicle category, the available vehicles data were time-aligned by speed for each driving cycle. Then, the average second-by-second speed, acceleration, emission rates, and fuel consumption were calculated averaging the values of the individual vehicles to create the composite vehicle data for each driving cycle.

IV. Calibration

The results presented refer to the composite vehicle characterized by Tier 1 emission standards[1], accumulated mileage greater than 50,000 miles, and high power/weight ratio. For this vehicle/technology category the values of the parameters needed in (4) are the following: A =0.1326 kW/m/s, B =2.7384e-03 kW/(m/s)^2, C =1.0843e-03 kW/(m/s)^3, and M = 1,325 kg (from [5]).

The calibration of EMIT has been conducted on a large spectrum of data, including stoichiometric, enrichment and enleanment conditions, in order to capture the emissions variability. The following set of composite data has been used: (a) FTP bag 2, (b) FTP bag 3, excluding the first 100 seconds (warm-up), and (c) first 900 seconds of MEC01.

A. *Engine-out emissions module*

An initial calibration of (6a) indicates that the coefficient of v^2 is negative, which is counterintuitive, but not statistically significant. This second order speed term should be small, since it mainly represents a higher order correction to the rolling resistance term. We then drop it in the calibration

[1] Tier 1 emission standards have been defined for light-duty vehicles in the Clean Air Act Amendments of 1990 and were phased-in progressively between 1994 and 1997. They are tested over the FTP cycle and expressed in g/mile.

process. Dropping it, the goodness of fit of the regression (6a) is practically unaffected (adjusted R-squared~0.96) and all coefficients are positive and statistically significant.

All regressions, with the exception of CO, give satisfactory results in terms of statistical significance and sign of most coefficients, as well as adjusted R-squared. For CO, the effect of enrichment is too distinct to be incorporated in the same equation. For enrichment conditions the emission rates are calculated as a linear function of the corresponding stoichiometric emission rates:

$$EO_{CO} = \begin{cases} EO_{CO}^{stoich} = \alpha_{CO} + \beta_{CO} v + \delta_{CO} v^3 + \zeta_{CO} av, & \\ \quad\quad if \quad 0 < P_{tract} \le P_{tract}^{enrich} & (10a) \\ \kappa + \chi \cdot EO_{CO}^{stoich}, \quad if \quad P_{tract} > P_{tract}^{enrich} & (10b) \\ \alpha'_{CO}, \quad if \quad P_{tract} = 0 & (10c) \end{cases}$$

The enrichment threshold P_{tract}^{enrich} is determined based on the cut-point in the trend of EO_{CO} versus FR (see Fig. 2). For (10a) it is necessary to employ a more 'robust' calibration, by removing a few outliers from the calibration data.

For HC, the emissions puffs data is omitted in the calculation of α'.

The calibrated parameters for Equations (6), (7), and (10) are shown in Table I. Engine-out emission rates (EO_i) are expressed in g/s, vehicle speed (v) is expressed in km/h, speed times acceleration (av) is expressed in m^2/s^3, and power is expressed in kW. We note the following:

- All coefficients have high t-statistics (greater than 2), except for β_{HC} and β_{CO} which have been dropped.
- All coefficients are, as expected, positive, except for α_{NOx}. The negative sign of α_{NOx} is consistent with the negative intercept of NO_x versus FR (see Fig. 2).

TABLE I
CALIBRATED PARAMETERS FOR THE ENGINE-OUT EMISSIONS MODULE.

	CO_2	CO	HC	NOx	FR
α	1.02 *(40.8)*	0.0316 *(22.8)*	0.00916 *(58.1)*	-0.00391 *(-3.7)*	0.365 *(26.1)*
β	0.0118 *(20.7)*	*(dropped)*	*(dropped)*	0.000305 *(11.4)*	0.00114 *(6.5)*
δ	1.92e-06 *(48.4)*	1.09e-07 *(49.9)*	7.55e-09 *(33.3)*	2.27e-08 *(14.0)*	9.65e-07 *(44.0)*
ζ	0.224 *(195.5)*	0.00883 *(43.0)*	.00111 *(60.5)*	0.00307 *(64.9)*	0.0943 *(150.3)*
α'	0.877	0.0261	0.00528	0.00323	0.299
κ		-6.10 *(-14.3)*			
χ		21.8 *(18.9)*			
P_{tract}^{enrich}		34			

t-statistics are reported in parentheses

B. *Tailpipe emissions module*

Equations (9a) and (9b) are calibrated using least square linear regressions. The calibrated parameters are shown in Table II.

TABLE II
CALIBRATED PARAMETERS FOR THE TAILPIPE CO_2 EMISSIONS MODULE.

α	1.11 *(47.0)*
β	0.0134 *(19.3)*
δ	1.98e-06 *(47.0)*
ζ	0.241 *(42.0)*
α'	0.973

t-statistics are reported in parentheses

The catalyst pass fractions for CO, HC and NO_x are modeled with the following piecewise linear functions.

$$CPF_{CO} = \begin{cases} 0 & if \quad EO_{CO} < z'_{CO} \\ m'_{CO} \cdot EO_{CO} + q'_{CO} & if \quad z'_{CO} < EO_{CO} < z''_{CO} \\ m''_{CO} \cdot EO_{CO} + q''_{CO} & if \quad EO_{CO} > z''_{CO} \end{cases} \quad (11)$$

$$CPF_{HC} = \begin{cases} q'_{HC} & if \quad EO_{HC} < z'_{HC} \\ m''_{HC} \cdot EO_{HC} + q''_{HC} & if \quad z'_{HC} < EO_{HC} < z''_{HC} \\ m'''_{HC} \cdot EO_{HC} + q'''_{HC} & if \quad EO_{HC} > z''_{HC} \end{cases} \quad (12)$$

$$CPF_{NOx} = m'_{NOx} \cdot EO_{NOx} + q'_{NOx} \quad (13)$$

Equations (11), (12) and (13) have been calibrated by minimizing the sum of the squared errors of the predicted tailpipe emissions obtained as the product of modeled catalyst pass fraction and measured engine-out emissions. The catalyst pass fraction functions are represented in Fig. 3. The calibrated coefficients are reported in Table II.

CPF_{HC} and CPF_{NOx} are challenging to model [8], [10]. CPF_{HC} is scattered especially for medium levels of engine-out emissions, where the highest values are related to high power episodes. CPF_{NOx} is especially noisy for very low engine-out emissions, with values ranging from nearly zero to ~0.95.

TABLE II
CATALYST PASS FRACTION CALIBRATION

m'_{CO}	1.15	q'_{CO}	-0.006	z'_{CO}	0.005
m''_{CO}	0.045	q''_{CO}	0.746	z''_{CO}	0.705
		q'_{HC}	0.0011	z'_{HC}	0.011
m''_{HC}	3.69	q''_{HC}	-0.031	z''_{HC}	0.047
m'''_{HC}	23.39	q'''_{HC}	-0.977		
m'_{NOx}	0.124	q'_{NOx}	0.067		

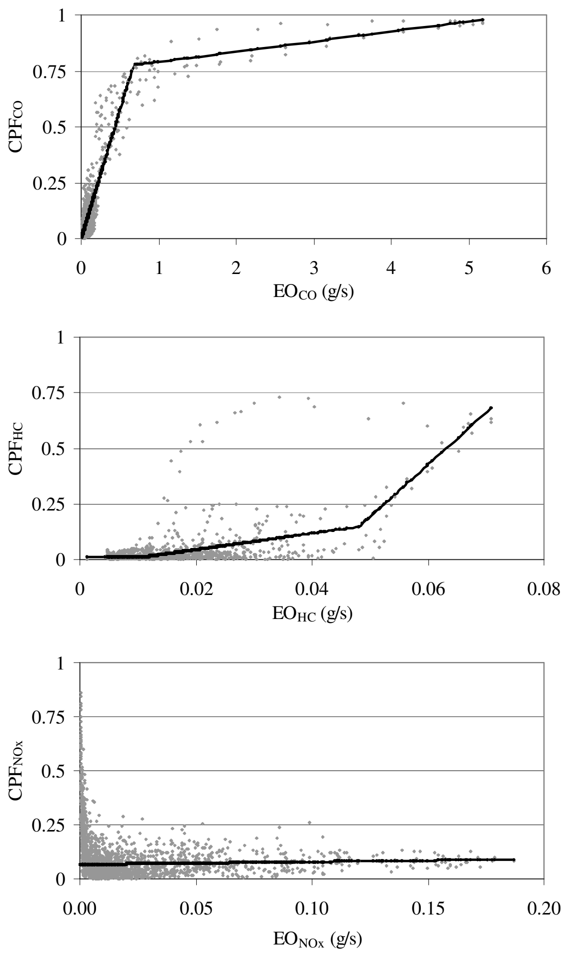

Fig. 3. Catalyst pass fraction for CO (a), HC (b), and NOx (c). The points represent the calibration data; the line represents the modeled CPF.

C. Results

The results of the calibration have been assessed looking at statistics such as the total percentage error over the cycles, and R^2 calculated on a second-by-second basis (see Table III and Table IV).

The estimated fuel consumption and CO_2 match the measurements satisfactorily (0.0% error and R^2~0.97).

For CO, the model fits the measurements quite well (R^2 ~0.90), resulting in a percentage error equal to -2.5% in engine-out and –6.4% in tailpipe emissions.

For HC, the model has a less desirable performance (R^2~0.60). For engine-out, as expected, the principal problem is represented by the enleanment puffs, which are not modeled, resulting in an underestimation of approximately -12%. For tailpipe, there is a tendency to overestimate the low emissions and underestimate the higher peaks. The resulting percentage error (-23.6%) is due not to enleanment puffs (which are not present in the measured tailpipe emissions), but to the underestimation of some peaks.

For NO_x, engine-out emissions fit well, while the fit for tailpipe emissions is lower (R^2 drops from 0.87 to 0.67 for category 9), due to the scattered behavior of CPF_{NOx}. However, the percentage error is very small (less than 2% in absolute value).

The predicted fuel consumption and tailpipe emissions are represented in Fig. 4 for a subset of the calibration data (FTP bag 2).

V. Validation

The validation of EMIT has been carried out on the composite US06 data. The results (see Table V, Table VI, and Fig. 5) are quite satisfactory, and comparable with those obtained using the output of the load-based model CMEM (version 2.01) [11] for the same vehicle/technology category[2].

TABLE III
EMIT CALIBRATION STATISTICS - ENGINE-OUT EMISSIONS

	CO_2	CO	HC	NOx	FR
Error (%)	0.0	-2.5	-12.3	0.9	0.0
R^2	0.97	0.90	0.63	0.87	0.97

TABLE IV
EMIT CALIBRATION STATISTICS - TAILPIPE EMISSIONS

	CO_2	CO	HC	NOx
Error (%)	0.0	-6.4	-23.6	-1.4
R^2	0.97	0.88	0.58	0.67

TABLE V
EMIT AND CMEM VALIDATION STATISTICS – ENGINE-OUT EMISSIONS

EMIT	CO_2	CO	HC	NOx	FR
Error (%)	-0.5	-2.2	-22.3	-0.4	5.3
R^2	0.95	0.50	0.22	0.83	0.95

CMEM	CO_2	CO	HC	NOx	FR
Error (%)	-4.5	20.6	4.7	-16.6	-2.2
R^2	0.90	0.48	0.17	0.67	0.81

TABLE VI
EMIT AND CMEM VALIDATION STATISTICS – TAILPIPE EMISSIONS

EMIT	CO_2	CO	HC	NOx
Error (%)	-2.2	6.5	26.5	-3.0
R^2	0.95	0.43	0.32	0.53

CMEM	CO_2	CO	HC	NOx
Error (%)	-6.5	36.1	80.3	32.0
R^2	0.88	0.33	0.20	0.33

Total fuel consumption and CO_2 are estimated with an error of 5.3% and -2.2% respectively, with a very high R^2 (0.95).

For CO, both the engine-out and the tailpipe modules overestimate some medium peaks and underestimate some high peaks. R^2 is higher than 0.40, and the percentage error is less than 7% in absolute value.

The HC model has the poorest performance among all species. In engine-out the principal problem is related to

[2] EMIT and CMEM are calibrated using similar sets of data. In EMIT this vehicle/technology category includes 9 vehicles, while it can be inferred from the documentation [5] that in CMEM one additional vehicle, which we omitted for lack of available data, is included. For the calculations reported in Tables V and VI we compared the output of the models with the composite vehicle data that we calculated aggregating the respective sets of vehicles.

enleanment puffs (total error equal to -22.3%) that, however, disappear in the measured tailpipe emissions. For tailpipe emissions there is a tendency towards underestimation of the high values and overestimation of the low values (total error equal to -26.5%).

For NO_x, engine-out emissions are well predicted, while the fit for tailpipe emissions is lower (R^2 drops from 0.83 to 0.53). However, the tailpipe total error is small (-3%).

VI. CONCLUSIONS

In this paper we presented EMIT, a dynamic model of emissions (CO_2, CO, HC, and NO_x) and fuel consumption for light-duty vehicles. The model was derived from the statistical and the load-based emissions modeling approaches, and effectively combines some of their respective advantages. EMIT was calibrated and validated for one vehicle category. The results indicate that the model gives reasonable results over an extensive range of operating conditions, compared to actual measurements as well as to results obtained with CMEM, a state-of-the-art load-based emission model. In particular, the model gives results with good accuracy for fuel consumption and carbon dioxide, reasonable accuracy for carbon monoxide and nitrogen oxides, and less desirable accuracy for hydrocarbons.

The structure and the calibration of EMIT are simpler compared with load-based models. While load-based models involve a multi-step calibration process of many parameters, and the prior knowledge of several readily available specific vehicle parameters, the approach presented in this paper collapses the calibration into few linear regressions for each emission species. Compared to a multi-step calibration, here the parameters directly optimize the fit to the emissions, avoiding error accumulations. Moreover, due to its relative simplicity, the model runs fast.

EMIT should next be calibrated for all categories available, including diesel cars. Moreover, data on heavy trucks, buses, and more recent vehicles, including possibly real-world measurements, are required in order to represent the actual emissions sources present on roadways. When data is available, particulate matter and air toxics will be modeled as well. Future studies should also address how to account for road grade, accessory usage and cold-start.

EMIT is suitable for integration with a variety of traffic models. Its capability of generating time-dependent estimates, given the time-dependent operating conditions of each vehicle, allows for applications that require a high spatial as well as temporal resolution. For example, it is possible to integrate in a straightforward fashion EMIT with a microscopic traffic simulator and a microscopic dispersion model to assess the impact of traffic management strategies on air quality.

Moreover, we have recently investigated the integration of instantaneous emission models such as EMIT with non-microscopic traffic models. We have proposed a methodology for this type of integration [12]. The methodology has been applied to integrate EMIT with a mesoscopic dynamic traffic flow model, which is developed in [13]. The integration is realized through an acceleration model, based on the statistical distribution of real-world acceleration data, which is developed in [14]. The combined traffic-acceleration-emission model has been applied to a hypothetical case study to illustrate its potential to estimate the effects of route guidance strategies, which are one of numerous examples of dynamic traffic management strategies, on traffic travel times and vehicle emissions. The first results of this application are presented in [12].

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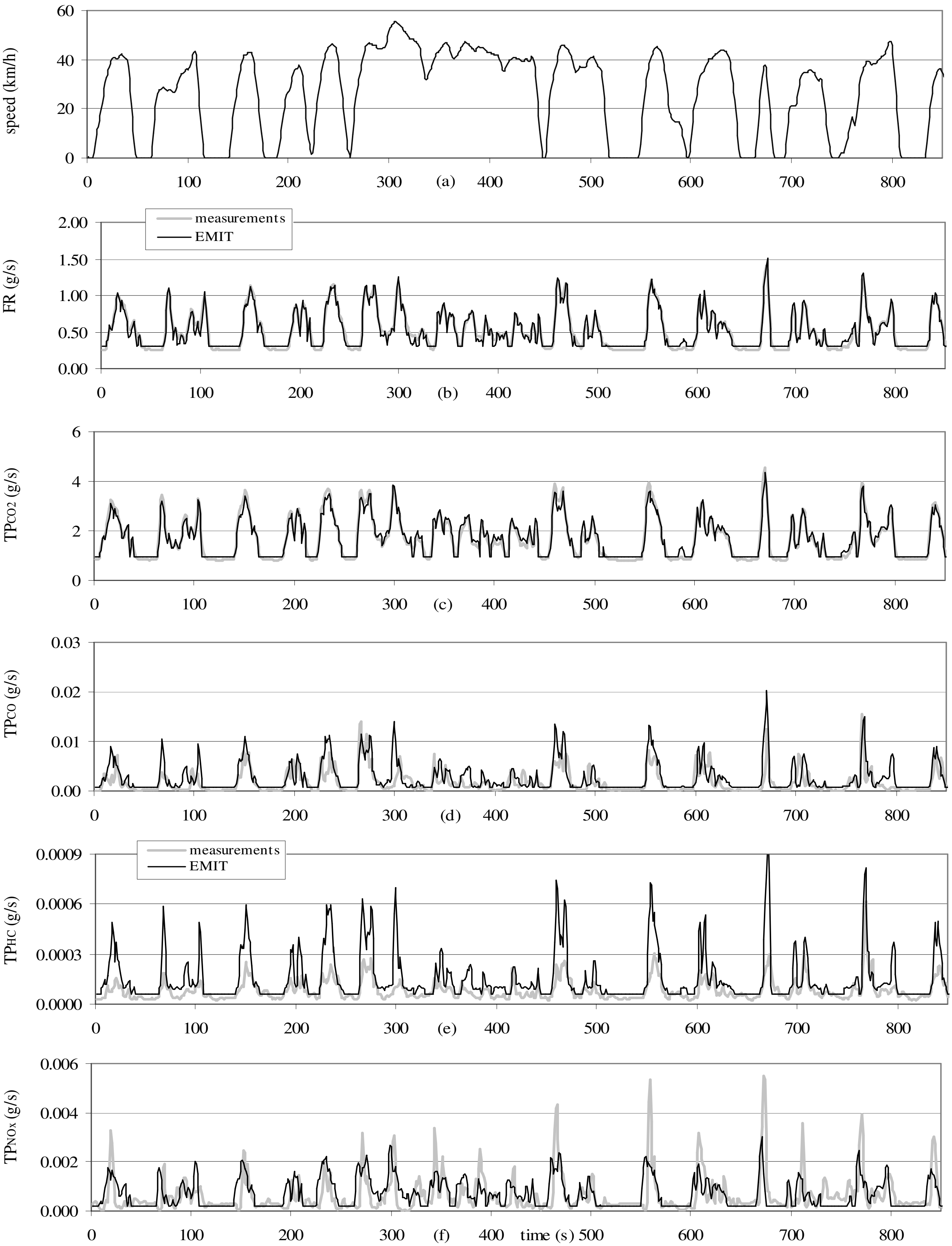

Fig. 4. Second-by-second fuel consumption and tailpipe emissions on FTP bag 2. Speed (a), FR (b), CO_2 (c), CO (d), HC (e), and NO_x (f) are represented. Light line: measurements; dark line: EMIT predictions.

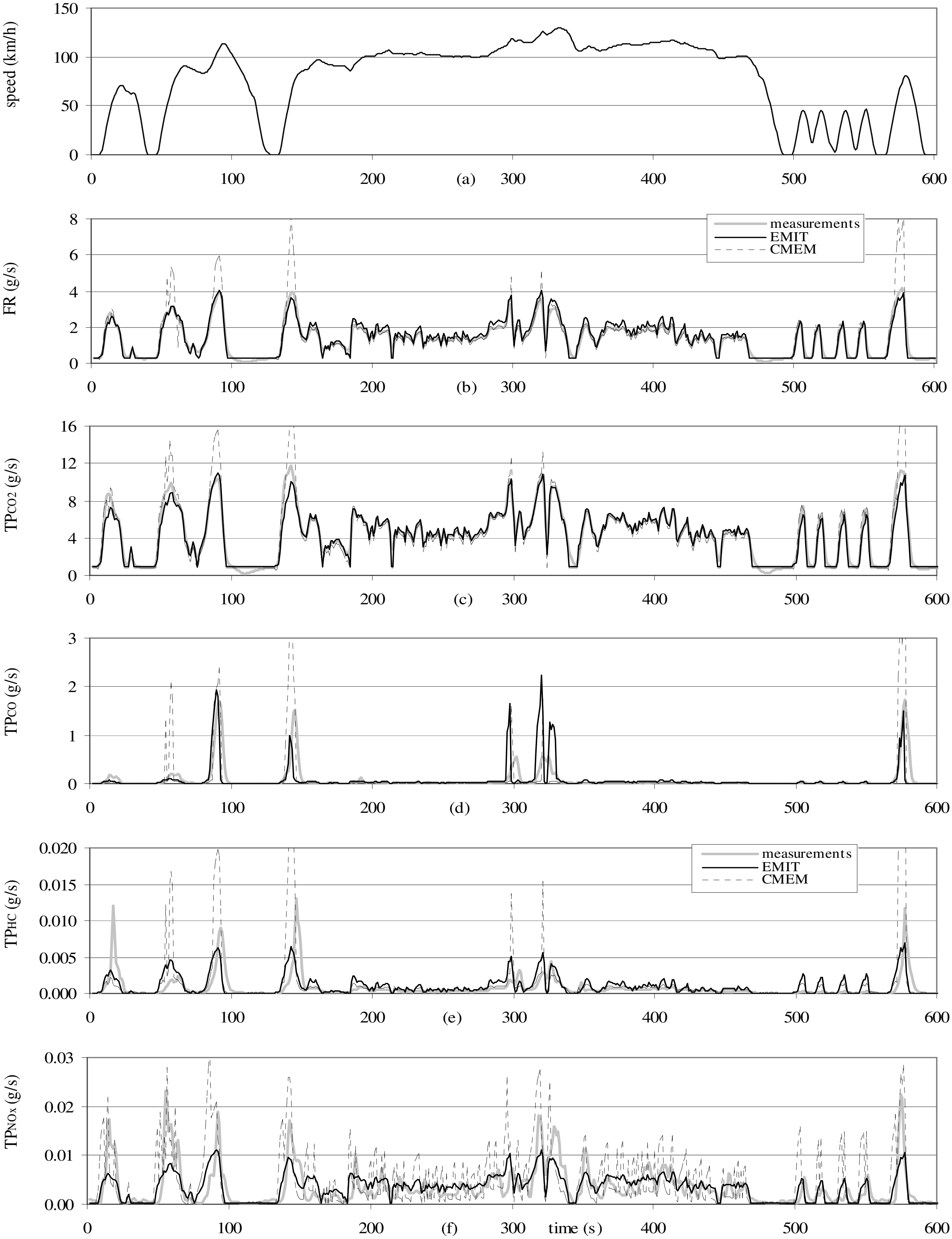

Fig. 5. Second-by-second fuel consumption and tailpipe emissions on the US06 cycle. Speed (a), FR (b), CO_2 (c), CO (d), HC (e), and NOx (f) are represented. Light line: measurements; dark line: EMIT predictions; dotted line: CMEM predictions.