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Virginia Tech Comprehensive Power-Based Fuel Consumption Model: Model development and testing

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ABSTRACT

Existing automobile fuel consumption and emission models suffer from two major drawbacks; they produce a bang–bang control through the use of a linear power model and the calibration of model parameters is not possible using publicly available data thus necessitating in-laboratory or field data collection. This paper develops two fuel consumption models that overcome these two limitations. Specifically, the models do not produce a bang–bang control and are calibrated using US Environmental Protection Agency city and highway fuel economy ratings in addition to publicly available vehicle and roadway pavement parameters. The models are demonstrated to estimate vehicle fuel consumption rates consistent with in-field measurements. In addition the models estimate CO_2 emissions that are highly correlated with field measurements.

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1. Introduction

The transportation sector is responsible for the consumption of about 30% of the energy in the US and this results in significant emissions of CO_2. One of the key strategies to improving vehicle fuel efficiency, and thus reducing emissions, is by obtaining more miles from each liter or gallon of fuel. A simple, accurate, and efficient fuel consumption model is useful in optimizing a vehicle's throttle and gear level to minimize the vehicle fuel consumption level over a future horizon; a predictive cruise control system.[1]

This paper outlines a power-based microscopic fuel consumption model, the Virginia Tech Comprehensive Power-Based Fuel Consumption Model (VT-CPFM) designed to overcome two main deficiencies of current models by addressing the ability to produce a control system that does not result in bang–bang control and allows easy calibration using publicly available data.

2. Microscopic fuel consumption modeling tools

Vehicle fuel consumption levels are typically derived from a relationship between instantaneous fuel consumption rates and instantaneous measurements of various explanatory variables including vehicle power, force (tractive effort), acceleration, speed, and/or roadway grade. Numerous fuel consumption models have been developed that incorporate explanatory

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[1] A recent McKinsey and Company (2009) report estimated that teaching consumers to eco-drive could fuel efficiency by 17%. Eco-driving comprises driving behaviors that maximize fuel economy and correspondingly reduce greenhouse gas emissions.

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variables to satisfy their specific objectives. One variable that stands out is vehicle power or vehicle specific power (VSP), which is the power exerted per unit mass. Vehicle power can be computed as the product of the force exerted by the vehicle and the vehicle velocity. The force includes both the net force and the force that is required to overcome the aerodynamic, rolling, and grade resistance forces. Assuming that the vehicle fuel consumption rate is proportional to the vehicle power, the fuel consumption can be estimated by computing the forces acting on the vehicle.

While the majority of fuel consumption models have been developed as power-demand models, the VT-Micro model is a statistical model from experimentation with numerous polynomial combinations of speed and acceleration levels to construct a dual-regime model (Ahn et al., 2002; Rakha et al., 2004). Apart from the VT-Micro model, most other models produce a bang–bang type of control system. This occurs because the partial derivative of the fuel consumption rate F with respect to the engine torque (T) is not a function of torque (Saerens et al., 2010) or $dF/dT \neq fT$. A model that results in a bang–bang control system would indicate that the optimum fuel economy control would be to accelerate at full throttle to reduce the acceleration time. This type of control, which is obviously incorrect, would recommend that the driver drive as aggressively as possible to minimize their fuel consumption level.

In addition, existing models require the calibration of their parameters by collecting vehicle-specific in-laboratory or field data. This exercise is time consuming, expensive, and does require vehicle instrumentation to gather the required data. The model addresses these two deficiencies in existing models, namely: the ability to result in a non-bang–bang control and the ability to calibrate the model parameters using publicly available fuel consumption and vehicle driveline data.

3. Comprehensive fuel consumption modeling framework

Vehicle fuel consumption depends on many factors that may not be captured easily by a single mathematical model. Some of the factors include: engine design, vehicle age, driver behavior, road topography, fuel properties, resistive forces on the vehicle, ignition technology, cylinder head design, friction inside the engine, temperature, humidity level, and many other factors. Compromising between simplicity and accuracy has always been a difficult task for any modeler so the challenge is to identify the key parameters for consideration in a model without creating a complicated model that poses a major calibration challenge.

One of the popular fuel consumption models that of Wong (2001) as formulated in Eq. (1) where the vehicle power is computed using Eq. (2).

$$F(t) = \mu\left(\frac{k\omega_e(t)d}{2000} + P(t)\right) \tag{1}$$

$$P(t) = \left(\frac{R(t) + ma(t)(1.04 + 0.0025\xi(t)^2)}{3600\eta_d} \cdot v(t)\right) \tag{2}$$

Here $F(t)$ is the fuel consumption rate (l/s) at time t; μ is the specific fuel consumption (kg/kJ/s), which varies with the engine condition; k is the engine friction in kilopascals (kPa); $\omega_e(t)$ is the engine speed in revolutions per second (rev/s) at time t; d is the engine displacement (l); and $P(t)$ is the power exerted by the vehicle driveline (kW) at time t and is computed using Eq. (2), where $R(t)$ is the resistance force (N), m is the vehicle mass (kg), $a(t)$ is the vehicle acceleration (m/s^2) at time t, $v(t)$ is the vehicle speed (km/h) at time t; ξ is the gear ratio at time t, and η_d is the driveline efficiency. This model, however, produces a bang–bang control system as was demonstrated earlier.

Engine friction (k) is generally proportional to the engine speed during a trip (Ross, 1997). However, it is difficult to obtain a relationship between engine friction (k) and engine speed for most vehicles without assistance from vehicle manufacturers. Consequently, it is typically assumed to be constant.

The resistance force on the vehicle is computed as the sum of the aerodynamic, rolling, and grade resistance forces as expressed in Eq. (3), where ρ is the density of air at sea level at a temperature of 15 °C (59°F) (equal to 1.2256 kg/m^3), C_D is the vehicle drag coefficient (unitless); C_h is a correction factor for altitude (unitless) and computed as 1–0.085H where H is the altitude (km); A_f is the vehicle frontal area (m^2); and C_r, c_1, and c_2 are rolling resistance parameters that vary as a function of the road surface type, road condition, and vehicle tire type (Table 1). The typical values of vehicle coefficients are (Rakha et al., 2001).

$$R(t) = \frac{\rho}{25.92}C_D C_h A_f v(t)^2 + 9.8066\,\mathrm{m}\frac{C_r}{1000}(c_1 v(t) + c_2) + 9.8066\,\mathrm{m}G(t) \tag{3}$$

The specific fuel consumption, which is the amount of fuel used per power unit produced, is typically observed from an engine performance graph, which is vehicle-specific (Edgar, 2008). In general, the specific fuel consumption varies as a function of the engine speed and has a parabolic shape. As engine speed increases, the specific fuel consumption rate decreases to a minimum value at engine speeds ranging between 2000 and 3500 rpm depending on the engine load and then increases again for higher engine speeds. This is because the engine is developed to produce its best performance and highest efficiency in the 2000–3500 rpm range. In addition engine friction loss is significantly higher at high engine speeds, causing an increase in the specific fuel consumption rate. The specific fuel consumption rate is also related to vehicle throttle levels. In the real world, vehicles do not typically operate at full engine load, but frequently change the throttle level. Even though the specific fuel consumption is a good concept to consider in the estimation of the fuel consumption rate, it is extremely

Table 1
Parameters required for model calibration.

Parameter	Required for VT-CPFM-1?	Required for VT-CPFM-2?	Value	Source
Model year	Yes	Yes		Auto website
Wheel radius	No	Yes		Auto website
Idling speed	No	Yes	600–750 rpm	Auto website
Redline speed	No	Yes		Auto website
Downshift speed	No	Yes	1500 rpm	Field data
Upshift speed	No	Yes	3400 rpm	Field data
Vehicle mass (kg)	Yes	Yes		Auto website
Drag coeff (C_D)	Yes	Yes		Auto website
Frontal area (A_f)	Yes	Yes	0.85 × height × width	Auto website
Rolling coefficient (C_r)	Yes	Yes	1.75	(Rakha et al., 2001)
c_1	Yes	Yes	0.0328	(Rakha et al., 2001)
c_2	Yes	Yes	4.575	(Rakha et al., 2001)
Driveline efficiency	Yes	Yes	85–95%	(Rakha et al., 2001)
Wheel slippage	Yes	Yes	2–5%	(Wong, 2001)
Number of cylinders	Yes	Yes		Auto website
Engine size (L)	Yes	Yes		Auto website
Number of gears	No	Yes		Auto website
Various gear ratios	No	Yes		Auto website
Final drive ratio	No	Yes		Auto website
Altitude (m)	Yes	Yes		GPS receiver
P_{mfo} (Pa)	Yes	Yes	400,000	(Wong, 2001)
Q (J/kg)	Yes	Yes	43,000,000	(Wong, 2001)

difficult to measure. The data in Fig. 1, gathered using an on-board diagnostic (OBD) reader, demonstrate that for positive power conditions the fuel consumption function is convex and could be modeled using a second-order polynomial model.

Two power-based second-order polynomial models are included here; the Virginia Tech Comprehensive Power-Based Fuel Consumption Model-1 and -2 (VT-CPFM-1 and VT-CPFM-2). The use of a second-order model with a positive second-order parameter is used to ensure that a bang–bang control does not result from the application of the model, as was described earlier in the paper. Addition of higher than second-order parameters would add to the complexity of the model and thus not allow for model calibration using the US Environmental Protection Agency (EPA) city and highway cycles. Consequently, a second-order model provides a good compromise between model accuracy and applicability.

The two VT-CPFM models are formulated as

$$FC(t) = \begin{cases} \alpha_0 + \alpha_1 P(t) + \alpha_2 P(t)^2 & \forall P(t) \geqslant 0 \\ \alpha_0 & \forall P(t) < 0 \end{cases} \tag{4}$$

and

$$FC(t) = \begin{cases} \beta_0 \omega_e(t) + \beta_1 P(t) + \beta_2 P(t)^2 & \forall P(t) \geqslant 0 \\ \beta_0 \omega_{idle} & \forall P(t) < 0 \end{cases} \tag{5}$$

where α_0, α_1, α_2 and β_0, β_1, and β_2 are vehicle-specific model constants that are calibrated for each vehicle and ω_{idle} is the engine idling speed (rpm). In the case of the VT-CPFM-1 model the power exerted at any instant t is computed using;

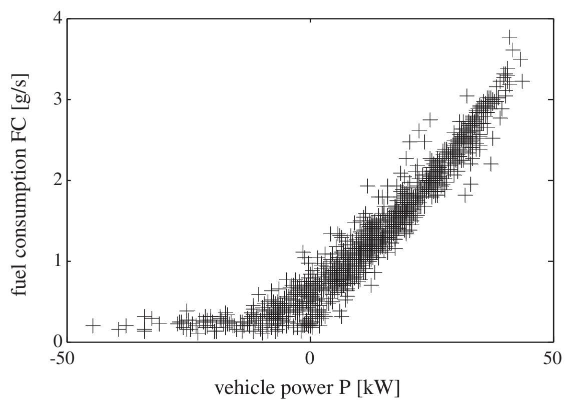


Fig. 1. Typical power vs. fuel consumption functional form.

$$P(t) = \left(\frac{R(t) + 1.04\ \mathrm{ma}(t)}{3600\eta_d}\right) v(t) \tag{6}$$

It should be noted that in comparing Eqs. (6) and (2), the $0.0025\xi^2$ term is dropped because the gear is unknown resulting in a slight loss of accuracy for the VT-CPFM-1 model. In the case of the VT-CPFM-2 model the driveline power is computed using Eq. (6).

The first model does not require any engine data because the power exerted by a vehicle is a function of the vehicle speed and acceleration level, which can be measured directly using non-engine instrumentation like, for example, a Global Positioning System (GPS). This model is ideal for implementation within microscopic traffic simulation software. This model, however, cannot be used to develop predictive eco- gear-shifting strategies given that changes in a vehicle's gear that results in changes in the engine speed would not be reflected in the fuel consumption estimates. The second model requires engine data in addition to external data and thus can be used to model eco-gear-shifting strategies but does require the explicit modeling of the vehicle driveline.

3.1. VT-CPFM-1 model

The idling fuel consumption rate for the VT-CPFM-1 model is estimated using Eq. (7) and bounded based on Eq. (8) to ensure that the functional form is convex, as will be discussed later in the paper. The idling fuel consumption rate in Eq. (7) is an average operating point method of Guzzella and Sciarretta. In reality the idling fuel consumption rate constantly fluctuates, however the model assumes, for simplicity purposes, that the rate remains constant.

$$\alpha_0 = \frac{P_{mfo}\omega_{idle}d}{22164 \times QN} \tag{7}$$

$$\alpha_0 = \max\left(\frac{P_{mfo}\omega_{idle}d}{22164 \times QN}, \frac{\left(F_{city} - F_{hwy}\frac{P_{city}}{P_{city}}\right) - \varepsilon\left(P_{city}^2 - P_{hwy}^2\frac{P_{city}}{P_{hwy}}\right)}{T_{city} - T_{hwy}\frac{P_{city}}{P_{city}}}\right) \tag{8}$$

where P_{mfo} is the idling fuel mean pressure (400,000 Pa); ω_{idle} is the idling engine speed (rpm); d is the engine displacement (liters); Q is the fuel lower heating value (43,000,000 J/kg for gasoline fuel); N is the number of engine cylinders; F_{city} and F_{hwy} are the fuel consumed for the EPA city and highway drive cycles (liters), (computed using Eqs. (9) and (10)); T_{city} and T_{hwy} are the durations of the city and highway cycles (1875 s and 766 s); P_{city} and P_{city}^2 are computed as the sum of power and power squared exerted each second over the entire cycle (computed using Eqs. (11) and (12)). Similarly, P_{hwy} and P_{hwy}^2 are estimated in the same manner for the highway cycle. The ε term ensures that the second-order parameter (α_2) is greater than zero. Experimentation with the model revealed that a minimum value of 1E-06 ensures that the optimum fuel economy cruising speed is in the 60–80 km/h range which is typical of light-duty vehicles.

$$F_{city} = \frac{3.7854 \times 17.663}{1.6093 \times FE_{city}} = \frac{41.5546}{FE_{city}} \tag{9}$$

$$F_{hwy} = \frac{3.7854 \times 16.4107}{1.6093 \times FE_{hwy}} = \frac{38.6013}{FE_{hwy}} \tag{10}$$

$$P_{city} = \sum_{t=0}^{T_{city}} P(t) \text{ and } P_{hwy} = \sum_{t=0}^{T_{hwy}} P(t) \tag{11}$$

$$P_{city}^2 = \sum_{t=0}^{T_{city}} P(t)^2 \text{ and } P_{hwy} = \sum_{t=0}^{T_{hwy}} P(t)^2 \tag{12}$$

It should be noted that the EPA started the use of additional drive cycles in 2008. These new tests—they had, in fact, been in use since the late 1990s but for emissions purposes only—are the US06 high-speed (80 mph max) cycle; the SC03, or "A/C" cycle, which is very similar to the city cycle but run in 95-degree heat with the vehicle's air conditioning active; and the cold FTP test, which is exactly the same as the city cycle but run at a temperature of 20 °C. Until the 2012 model year, automakers run the tests on the old drive cycles but report the fuel-economy ratings for the new cycles using Eqs. (13) and (14) developed by the EPA. Here FE_{city} and FE_{hwy} are the fuel economy estimates for the old cycles while FE'_{city} and FE'_{hwy} are the estimates for the new drive cycles. It should be noted that the units of FE are in mi/gal in the case of US cycles.

$$FE'_{city} = \frac{1}{\frac{1.18053}{FE_{city}} + 0.003259} \tag{13}$$

$$FE'_{hwy} = \frac{1}{\frac{1.3466}{FE_{hwy}} + 0.001376} \tag{14}$$

The parameter α_2 has to be greater than zero in order to ensure that the model does not produce a bang-bang control (Saerens et al., 2010). This requirement introduces the constraint of Equation (15). The α_1 parameter can then be computed using Equation (16). It should be noted that Equation (15) produces the lower limit presented in Equation (8).

$$\alpha_2 = \frac{\left(F_{city} - F_{hwy}\frac{P_{city}}{P_{hwy}}\right) - \left(T_{city} - T_{hwy}\frac{P_{city}}{P_{hwy}}\right)\alpha_0}{P_{city}^2 - P_{hwy}^2\frac{P_{city}}{P_{hwy}}} \geqslant \varepsilon = 1\text{E-}06 \tag{15}$$

$$\alpha_1 = \frac{F_{hwy} - T_{hwy}\alpha_0 - P_{hwy}^2\alpha_2}{P_{hwy}} \tag{16}$$

Once α_0 is computed, the remaining two model coefficients (α_1, α_2) can be estimated using the fuel economy ratings for the EPA city and highway drive cycles. As shown in Eq. (17), the two variables α_1 and α_2 can be computed by solving a system of linear equations;

$$\begin{aligned} F_{city} &= T_{city}\alpha_0 + P_{city}\alpha_1 + P_{city}^2\alpha_2 \\ F_{hwy} &= T_{hwy}\alpha_0 + P_{hwy}\alpha_1 + P_{hwy}^2\alpha_2 \end{aligned} \tag{17}$$

A Matlab code has been developed that allows the user to input various vehicle parameters to calibrate the model coefficients, as illustrated in Fig. 2. The user has the ability to input both US and European fuel economy ratings. In the case of the US drive cycles the standard city and highway cycles are used with the adjustments derived in Eqs. (18) and (19) for 2008 and later model years.

$$FE_{city} = \frac{1.18053}{\frac{1}{FE'_{city}} - 0.003259} \tag{18}$$

$$FE_{hwy} = \frac{1.3466}{\frac{1}{FE'_{hwy}} - 0.001376} \tag{19}$$

In the case of European vehicles the European drive cycles are used. The New European Drive Cycle is a driving cycle consisting of four repeated ECE-15 driving cycles and an Extra-Urban driving cycle, or EUDC. The NEDC attempts to represent the

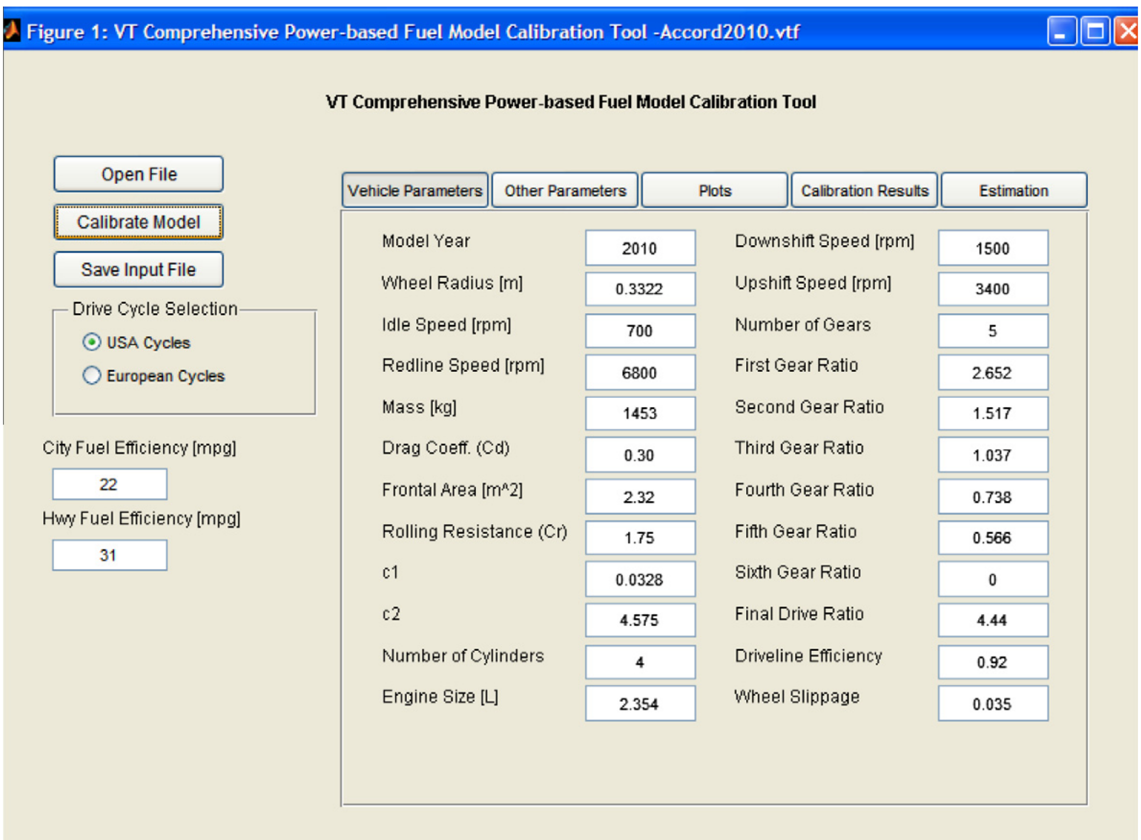


Fig. 2. Illustration of VT-CPFM calibration tool.

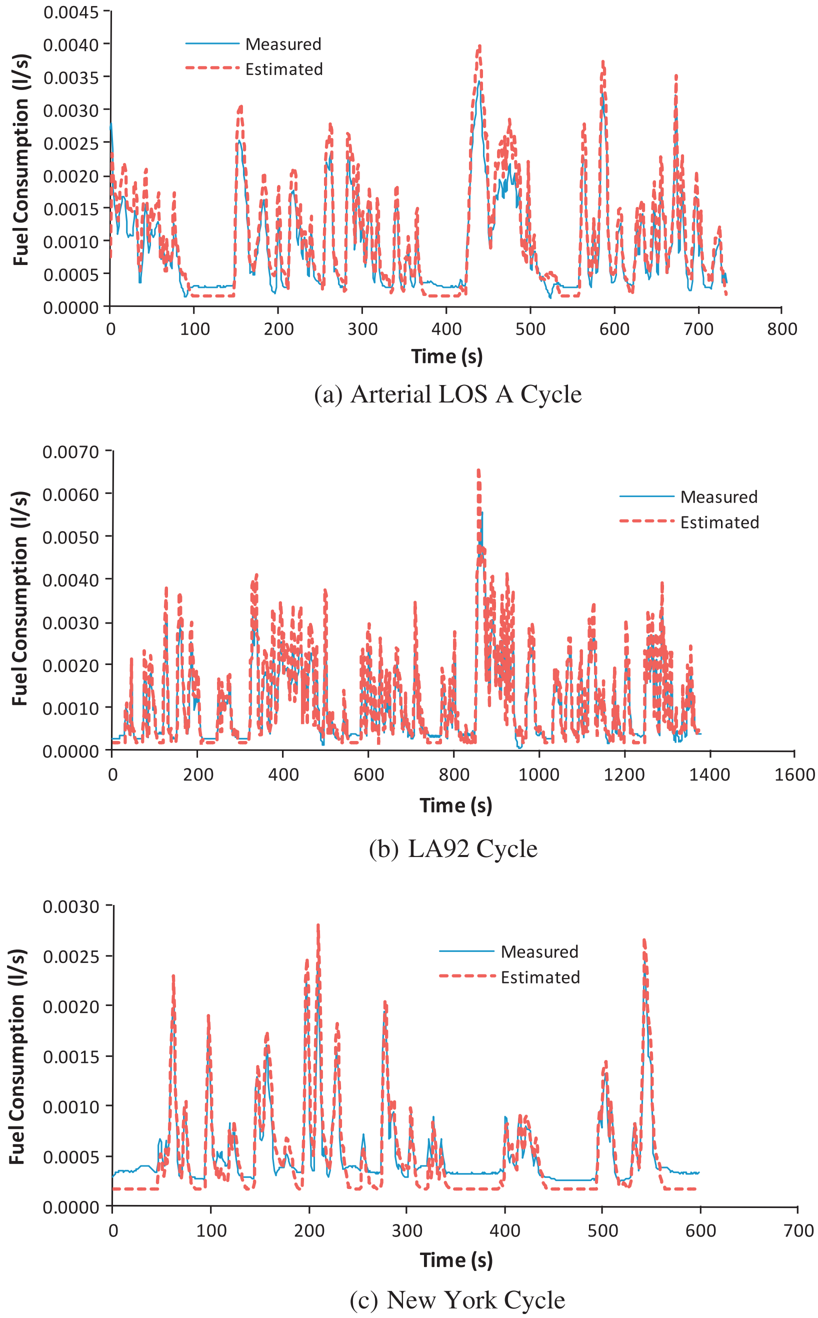


Fig. 3. Instantaneous model validation, Honda Accord.

typical usage of a vehicle in Europe, and is used, among other things, to assess the emission levels of car engines. It should be noted that in case of the European cycles the fuel ratings are reported in liters per 100 km.

Fig. 2 and Table 1 show the input parameters for a 2010 Honda Accord vehicle. The data include parameters for the estimation of the various resistance forces in addition to gear data that are used for the VT-CPFM-2 model to compute the engine speed as a function of the vehicle speed and engaged gear. It should be noted that the data values and sources are summarized in Table 1. Some model parameters may be assumed as will be described. The engine efficiency accounts for the power losses in the engine due to internal friction and other factors. This factor ranges between 15% and 5% for light- and heavy-duty vehicles. The frontal area of the vehicle can be approximated as 85% of the vehicle height multiplied by its width if it is not given directly in the vehicle specifications. The air drag coefficient is typically provided on auto manufacturer websites, however when not available typical values for light-duty vehicles range from 0.30 to 0.35, depending on the aerodynamic

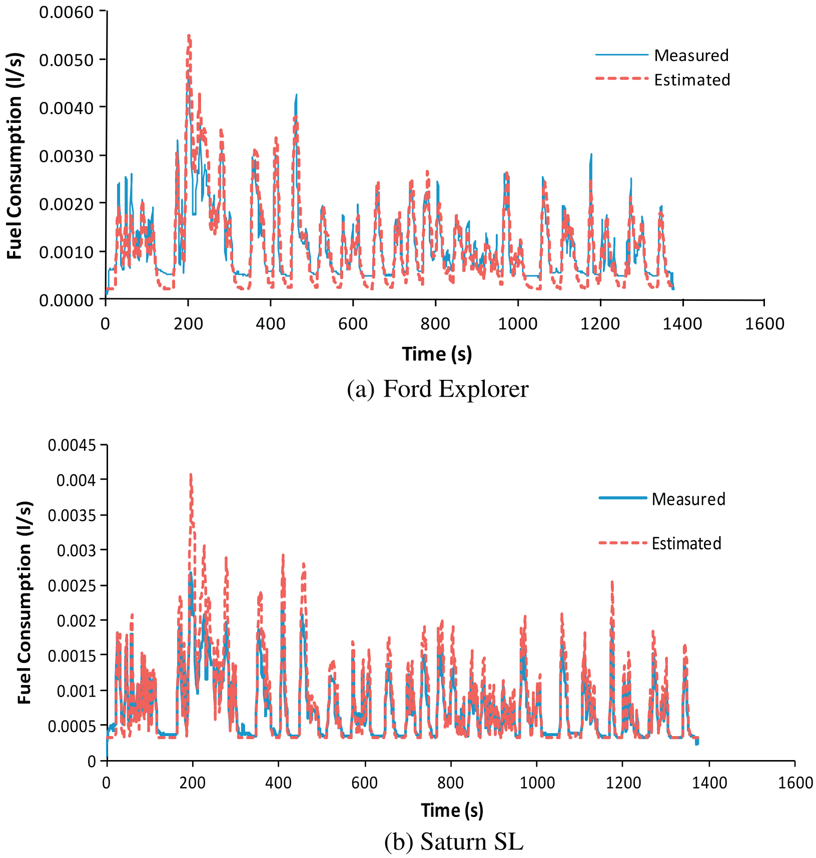


Fig. 4. Instantaneous model validation, City Cycle.

features of the vehicle. Heavy-duty vehicles have higher drag coefficients ranging from 0.58 to 0.78. The tire size for a Honda Accord is reported as P215/60 R16 on the Honda website. The 215 parameter is the tire width in millimeters, measured from the bottom of the bead to the bottom of the bead, the 60 is the sidewall aspect ratio, the ratio of sidewall height to tire width at the tread (indicating that the sidewall height is 60% of the tread width), and the 16 is the wheel rim diameter in inches. Consequently, in this example the tire radius is computed as 33.22 cm.

3.2. VT-CPFM-2 model

The VT-CPFM-2 model can be calibrated in a similar fashion. The engine speed coefficient is computed as:

$$\beta_0 = \max\left(\frac{P_{mfo}d}{22164 \times QN}, \frac{\left(F_{city} - F_{hwy}\frac{P_{city}}{P_{city}}\right) - \varepsilon\left(P_{city}^2 - P_{hwy}^2\frac{P_{city}}{P_{hwy}}\right)}{\omega_{city} - \omega_{hwy}\frac{P_{city}}{P_{hwy}}}\right) \tag{20}$$

The two remaining parameters can then be calibrated using the EPA fuel economy ratings for the city and highway cycle using

$$\beta_1 = \frac{\left(\frac{F_{city} - \omega_{city}\beta_0 - P_{city}^2\beta_2}{P_{city}}\right) + \left(\frac{F_{hwy} - \omega_{hwy}\beta_0 - P_{hwy}^2\beta_2}{P_{hwy}}\right)}{2} \tag{21}$$

$$\beta_2 = \frac{\left(F_{city} - F_{hwy}\frac{P_{city}}{P_{hwy}}\right) - \left(\omega_{city} - \omega_{hwy}\frac{P_{city}}{P_{hwy}}\right)\beta_0}{P_{city}^2 - P_{hwy}^2\frac{P_{city}}{P_{hwy}}} \geqslant 1\text{E} - 06 \tag{22}$$

where the terms are as before except ω_{city} and ω_{hwy} that are computed using.

$$\omega_{city} = \sum_{t=0}^{T_{city}} \omega(t) \tag{23}$$

$$\omega_{hwy} = \sum_{t=0}^{T_{hwy}} \omega(t) \tag{24}$$

Again the Matlab code provides an automated tool for the calibration of the model parameters for both North American and European vehicles.

4. Model validation

4.1. Instantaneous fuel consumption estimates

The vehicles tested are a Ford Explorer (4.0 L, 2223 kg), Saturn SL (1.9 L, 1240 kg), and Honda Accord (2.2L, 1605 kg); a light-duty truck and two light-duty passenger cars. The vehicles are run on a chasis dynamometer: the arterial level of service (LOL) A cycle, the LA92 cycle, and the New York cycle. These cycles are selected for validation purposes because they represent a wide range of real-world driving conditions. The arterial LOS A (ARTA) drive cycle involves several full and partial stops in addition to travel at a fairly high speed, representing the normal driving conditions of arterial and/or collector roads. The LA92 cycle, or unified driving schedule, developed by the California Air Resources Board and. compared to the FTP, the LA92 has a greater top speed, a greater average speed, less idle time, fewer stops per distance, and a greater acceleration level. The New York City cycle features low-speed, stop-and-go traffic conditions and involves more aggressive and realistic driving behavior for congested urban areas.

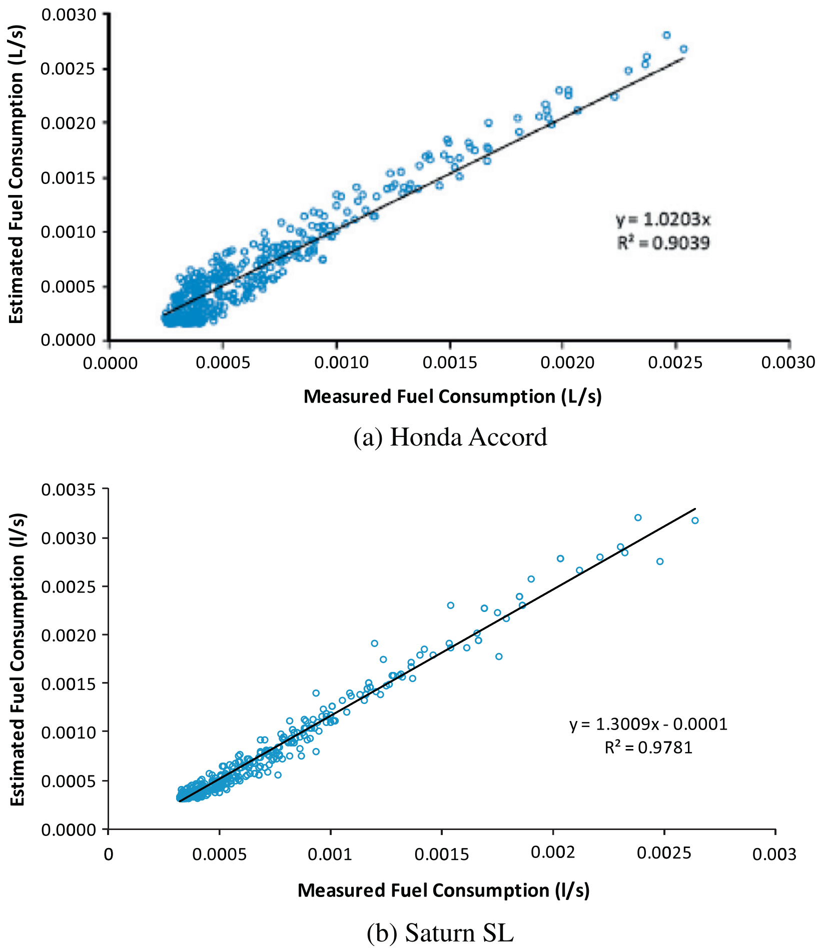
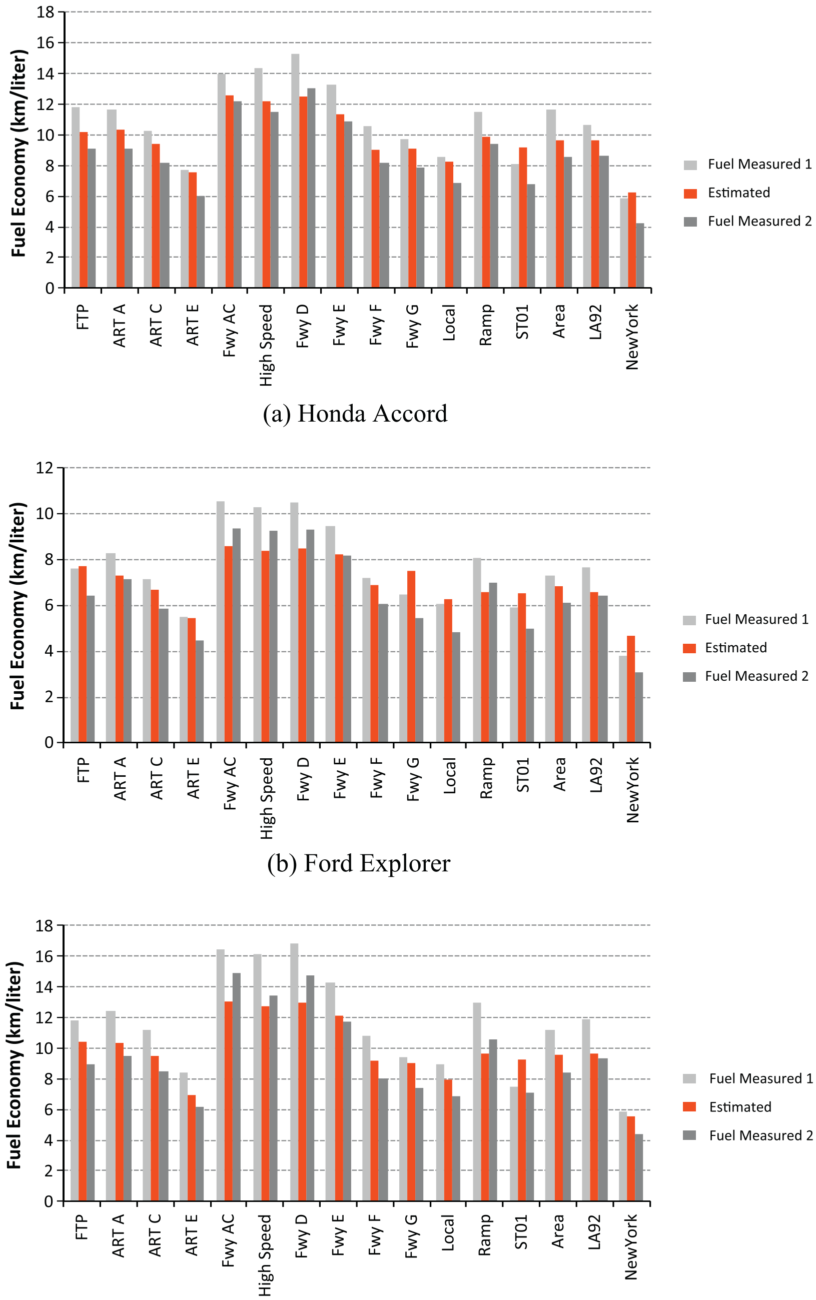


Fig. 5. Instantaneous model validation, New York City Cycle.

The instantaneous measured and estimated fuel consumption rates are compared by running the test vehicles on the three drive cycles; Figs. 3 and 4. Superimposed on the figures are the VT-CPFM-1 model estimates, which were computed using each of the vehicle-specific parameters. To capture the temporal autocorrelation in fuel consumption levels, an exponential smoothing filter was applied. The smoothing process combines α% (smoothing parameter) of the newly estimated instantaneous fuel consumption level from the VT-CPFM model with $(1-\alpha)$% of the fuel consumption of the previously smoothed estimate. The smoothing parameter is optimized by minimizing the sum of squared error between estimated and field measured fuel consumption levels. In the case of the Honda Accord and Saturn SL the optimum smoothing factors is 45% and 15% for the Ford Explorer. Based on experimentation with various vehicles, a smoothing factor of 20% was found to provide a level of autocorrelation consistent with field observations.



(a) Honda Accord

(b) Ford Explorer

(c) Saturn SL

Fig. 6. Simulated fuel economy for driving cycles.

The predicted fuel consumption rates generally follow the peaks and valleys of the measured data and demonstrate a good agreement with field measurements. While it appears that the model slightly overestimates some fuel consumption rates for the City cycle, in general the model predictions follow the field-collected fuel measurements with high correlation coefficients, as illustrated in Fig. 5. Specifically, in the case of the New York cycle, in which a slope of 1.0 indicates a close match between predicted and measured fuel consumption levels.

4.2. Trip level

The model estimates are compared to field collected fuel consumption data gathered by the EPA. The validation effort involves an aggregated trip level comparison over 16 drive cycles using three test vehicles that were utilized for the instantaneous model validation, as illustrated in Fig. 6. The database includes many off-cycle (non-FTP) fuel data over facility types and therefore provides a good assessment of the quality of model estimates for roadway types and levels of congestion.

Fig. 6 gives the model estimates and two EPA's field data for driving cycles; measured 1 representing the fuel consumption data under FTP ambient conditions using the standard vehicle certification test fuel and measured 2 the extreme conditions that consume more fuel than normal driving condition. In addition, the central bars illustrate the model fuel economy estimates for the three test vehicles. The figure shows a good fit between the model estimates and the field measurements. Specifically, the predictions typically lay within field measurements. Further, the model generally follow the average field data of the test vehicle fuel economy under driving conditions and, hwy AC, high speed, and hwy D cycles generate good fuel economy trips while the fuel economy values of ART E and New York cycles are relatively lower than other trip cycles.

4.3. Optimum cruise speed

In validating the model, a comparison was made to the VT-Micro model estimates for the Oakridge National Laboratory (ORNL) average vehicle. The ORNL test vehicles were driven in the field to verify their maximum operating boundary. Subsequently, vehicle fuel consumption and emission rates were measured in a laboratory on a chassis dynamometer within the vehicle's feasible vehicle speed and acceleration envelope. Data sets were generated that included vehicle energy consumption and emission rates as a function of the vehicle's instantaneous speed and acceleration levels. Several measurements were made to obtain an average fuel consumption and emission rate (West et al., 1997). The eight normal emitting vehicles included five light-duty automobiles and three light duty trucks. These vehicles were selected to produce an average vehicle that was consistent with average vehicle sales in terms of engine displacement, vehicle curb weight, and vehicle type (West et al., 1997). Specifically, the average engine size was 3.3 l, the average number of cylinders was 5.8, and the average curb weight was 1497 kg (3300 lbs). Industry reports show that the average sales-weighted domestic engine size in 1995 was 3.5 l, with an average of 5.8 cylinders.

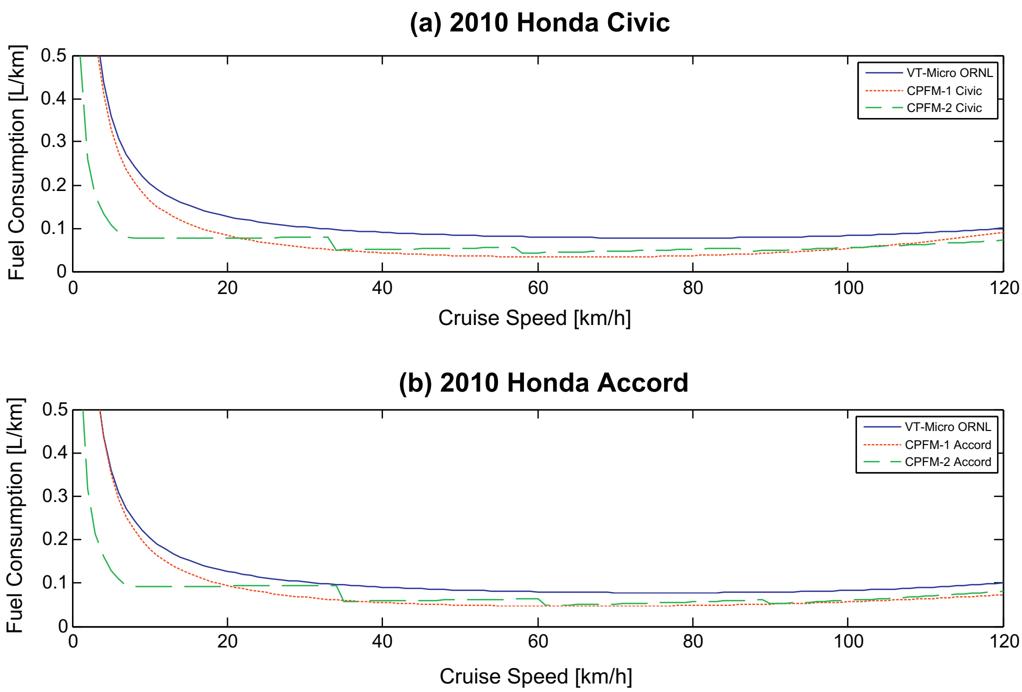


Fig. 7. Impact of cruise speed of vehicle consumption rate.

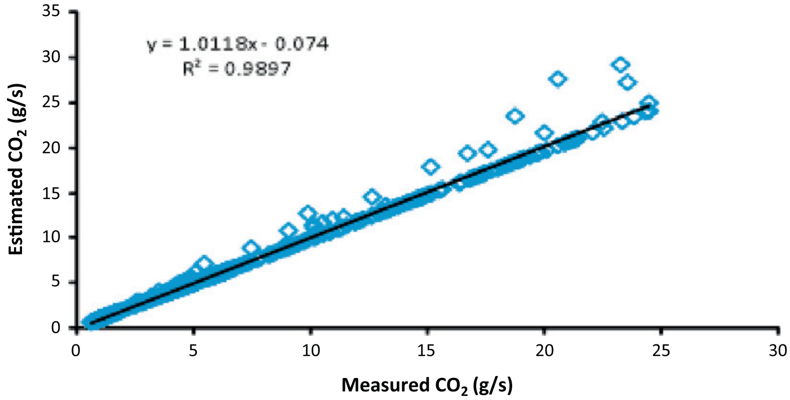
As illustrated in Fig. 7 the VT-CPFM-1 and VT-CPFM-2 models are consistent with the VT-Micro predictions of optimum cruise speeds and produce the same bowl shaped curve as a function of vehicle cruise speed. Specifically, the optimum speed ranges between 60 and 80 km/h for the two test vehicles (2010 Honda Civic and Accord). It should be noted that the VT-CPFM fuel consumption estimates are lower because the vehicles that were modeled are newer and thus more efficient vehicles.

5. CO_2 emissions

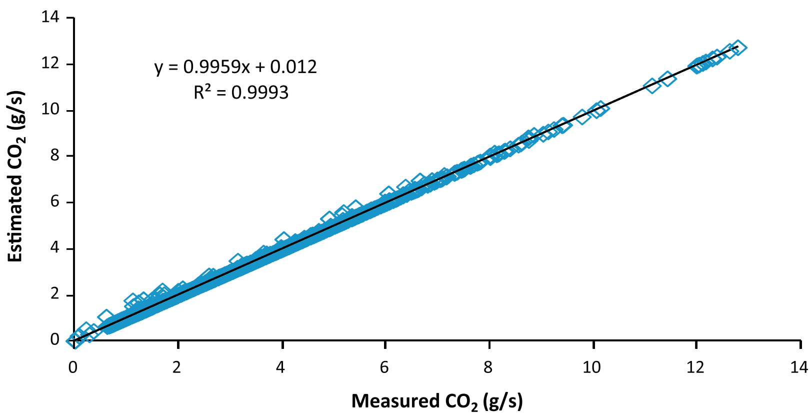
Using Eq. (13), CO_2 emissions can be estimated from the carbon balance equation using fuel consumption and HC and CO emissions. Since the absolute value of CO_2 emissions is significantly higher than HC and CO emissions, the prediction of CO_2 emissions is primarily affected by the fuel consumption level. To calibrate the CO_2 emission rate, a Ford Crown Victoria test vehicle was tested using on-board emission measurement (OEM) equipment. The data were collected from the Route 460 Bypass between Christiansburg and Blacksburg, Virginia. The field data collection involved running the test vehicle at a constant speed (104 km/h) along the Route 460 Bypass. The test vehicle was accelerated from a complete stop and continued to accelerate until the vehicle reached a speed of 104 km/h at a normal acceleration level and decelerated to a complete stop. Eleven valid trip repetitions were made to ensure that sufficient data were available. Eq. (2) is used to estimate the CO_2 emission level for all 11 trips. The value of the estimated parameter is almost identical to the value derived from the carbon balance equation without HC and CO emissions. The θ parameter is found to be 2330 when CO_2 emissions are in g/s and fuel consumption estimates are in l/s.

$$\theta = \frac{\sum_{t=0}^{T} CO_2(t)}{\sum_{t=0}^{T} F(t)} \tag{25}$$

Two data sets are employed in Fig. 8 to compare the actual CO_2 emissions to the estimated. The data in Fig. 8a are from Route 460, with the second set collected on a dynamometer by the EPA along the LA04 cycle, also known as the city cycle. There is



(a) Ford Crown Victoria: Route 460 OEM Data



(b) Ford F150 Truck: LA04 Cycle

Fig. 8. CO_2 estimation using fuel consumption rate.

good agreement between the predicted and measured CO_2 emissions. Specifically the model estimated the CO_2 emission within a 2% error range, and the coefficients of correlation of the two examples were measured at up to 99% along the Route 460 trips and LA04 cycle.

6. Conclusions

The research presented in this paper develops two simple fuel consumption models that do not result in a bang–bang control system and that can be calibrated easily using publicly available data. Specifically, the models can be calibrated using the Environmental Protection Agency city and highway fuel economy ratings that are publicly available. The models are demonstrated to estimate vehicle fuel consumption rates consistent with in-field measurements. Finally, a procedure for estimating CO_2 emissions is developed producing emission estimates that are highly correlated with field measurements.

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