Fuel consumption model for heavy duty diesel trucks: Model development and testing

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Fuel Consumption Model for Heavy Duty Diesel Trucks: Model Development and Testing

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Abstract

A simple, efficient, and realistic fuel consumption model is essential to support the development of effective eco-freight strategies, including eco-routing and eco-driving systems. The majority of the existing heavy duty truck (HDT) fuel consumption models, however, would recommend that drivers accelerate at full throttle or brake at full braking to minimize their fuel consumption levels, which is obviously not realistic. To overcome this shortcoming, the paper applies the Virginia Tech Comprehensive Power-based Fuel consumption Model (VT-CPFM) framework to develop a new model that is calibrated and validated using field data collected using a mobile emissions research laboratory (MERL). The results demonstrate that the model accurately predicts fuel consumption levels consistent with field observations and outperforms the comprehensive modal emissions model (CMEM) and the motor vehicle emissions simulator (MOVES) model. Using the model it is demonstrated that the optimum fuel economy cruise speed ranges between 32 to 52 km/h with steeper roads and heavier trucks resulting in lower optimum cruise speeds. The results also demonstrate that the model generates accurate CO_2 emission estimates that are consistent with field measurements. Finally, the model can be easily calibrated using data collected using non-engine instrumentation (e.g. Global Positioning System) and readily implemented in traffic simulation software, smartphone applications and eco-freight programs.

Keywords: Heavy Duty Diesel Truck, Fuel Consumption Model, Eco-Routing, Eco-Driving, Optimum Cruise Speed

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1. Introduction

Transportation activities account for 28% of the total U.S. energy use and 33.4% of carbon dioxide (CO_2, the major component of greenhouse gas (GHG) emissions) production (Davis et al. (2015); EPA (2015)). Consequently, numerous efforts are being tested in an attempt to reduce transportation-related energy use and GHG emissions in response to global energy and environmental issues (e.g. global warming). As the largest emitter of CO_2 (42.7%) in the transportation sector, passenger cars have attracted significant attention in the past decade, and reduction in fuel consumption and emission levels have been achieved through the development of relevant regulations and technical solutions. As a counterpart, however, the investigation of heavy duty diesel truck (HDDT) fuel consumption behavior is relatively less mature compared to that of gasoline passenger cars. Although HDDTs make up only a fraction of the total vehicle population, they are major contributors to GHG emissions, accounting for 22.8% of the total CO_2 production in the transportation sector (EPA (2015)).

Currently, HDDTs are receiving increasing attention from legislators, the government and society at large. For example, in September 2011, the National Highway Traffic Safety Administration (NHTSA) and the U.S. Environmental Protection Agency (EPA) jointly promulgated the first-ever federal regulations mandating improvements in fuel economy of heavy-duty commercial vehicles (Harrington and Krupnick (2012); U.S. EPA and NHTSA (2011)). Furthermore, researchers have been committed to developing road eco-freight strategies (Pindilli (2012); Lattemann et al. (2004); Dzenisiuk (2012); Takada et al. (2007)) in order to support "green transportation" policy making.

An accurate and efficient fuel consumption model is needed to provide robust fuel estimates in support of quantifying potential reductions in fuel consumption and emission levels induced by implementing eco-friendly strategies, such as developing eco-routing (Rakha et al. (2012); Boriboonsomsin et al. (2012); Ahn and Rakha (2013)) or eco-driving systems (Schall and Mohnen (2015); Saboohi and Farzaneh (2009); Soylu (2014); Barkenbus (2010); Ahn et al. (2011)) and utilizing advanced fuel techniques (Wayne et al. (2004); Guo et al. (2015); Onat et al. (2015)) or alternative fuels (Rakopoulos et al. (2015); Balat and Balat (2009); Demirbas (2007); López et al. (2009)). Among the existing modeling efforts, most are operated at a macroscopic or microscopic level. The macroscopic models, such as MOBILE 6.2 (Arbor (2003)), were demonstrated to produce unreliable estimates due to their inability of capturing transient vehicle activities (Ahn and Rakha (2008)). Consequently, they are incapable of being utilized for the energy and environmental assessment of traffic operational projects. Microscopic models were introduced in order to better capture the variability in fuel consumption and GHG emissions associated with vehicle dynamics. A wide range of instantaneous models have been developed using in-laboratory or field data, and some of them are applicable to modeling HDDTs, such as

MOVES, VT-Micro (Rakha et al. (2004)), the Passenger Car and Heavy Duty Emission Model (PHEM) (Hausberger et al. (2010)), VERSIT (Smit et al. (2007)), and the Comprehensive Modal Emissions Model (CMEM) (Barth et al. (2000, 2004)).

The majority of the aforementioned models, however, have intrinsic limitations. For example, MOVES, which was developed as an inventory model based on a wide range of data sources, is capable of providing robust estimates. Nonetheless, it requires massive user inputs for each run, which significantly increases the time required to run multiple scenarios and large networks. CMEM generally underestimates fuel consumption levels for acceleration maneuvers; more importantly, it characterizes fuel consumption as a linear function of vehicle power (positive power section), which produces a bang-bang type of control system. A bang-bang control may arise when the partial derivative of the response with respect to the control variable is not a function of the control variable (a more detailed description of a bang-bang control system is provided in section 2). The fuel estimate module for CMEM is addressed in Eq.(1):

$$FR = \frac{K \cdot N \cdot V + P/\eta}{43.2} \cdot [1 + b_1 \cdot (N - N_0)^2] \tag{1}$$

Here FR is the fuel rate in g/s, K is the engine friction factor, N is engine speed in (revolutions per second), V is engine displacement in liters, η is the efficiency for diesel engines, b_1 equals to 1×10^{-4}, N_0 is a constant related to engine displacement, $43.2KJ/g$ is the lower heating value of a typical diesel fuel, and P is the vehicle power which is the control variable of the fuel model. Since the fuel rate is linearly related to the vehicle power, its partial derivative with respect to power is independent of the power. This may suggest that drivers accelerate at full throttle to reduce acceleration time in order to minimize their trip fuel consumption levels. Similarly, PHEM and VERSIT produce a bang-bang control as well. VT-Micro is capable of circumventing the bang-bang control; however, it requires a large amount of in-laboratory or field data to be calibrated, which is cost-prohibitive and time-consuming.

Overall, the existing models either produce a bang-bang type of control (either full throttle or zero throttle input) system or cannot be easily calibrated or efficiently used. Consequently, a simple, accurate and efficient model is needed. Rakha et al. (2011) developed the Virginia Tech Comprehensive Power-based Fuel consumption Modeling (VT-CPFM) framework by characterizing fuel consumption levels as a second-order polynomial function of vehicle power to circumvent the bang-bang control problem. Furthermore, the model offers a unique ability to be calibrated using publicly available data (a more detailed description of the calibration procedure is provided in Rakha et al. (2011) withou data collection. Recent efforts have validated the applicability of the model for light duty vehicles (LDVs) (Park et al. (2013)) and transit buses (Wang and Rakha (2016a,b)) under real-world driving conditions; however, it has not been expanded to HDDTs yet. Consequently, the paper is intended to develop the VT-CPFM-based model for HDDTs in order to circumvent the bang-bang problem in the family of heavy duty truck (HDT) fuel consumption modeling tools. The developed model will be applied to develop eco-routing and eco-driving systems in future studies.

2. A Bang-bang Control System

Minimizing fuel consumption levels, from the system perspective, is essentially an optimal control problem that attempts to compute the optimal solution with the control variable restricted to being between a lower and an upper bound. In optimal control problems, a bang-bang solution may occur when a control switches abruptly from one extreme to the other. To mathematically give a complete picture of the bang-bang control, the minimum-fuel problem is described in Eq.(2), which is derived from Pontryagin's Maximum Principle (Pontryagin (1987); Saerens et al. (2010)):

$$\min_{P(.),t_e} \quad \int_0^{t_e} \dot{m}_f(P(t))dt \tag{2a}$$

$$subject\ to : P_{min}(t) \le P(t) \le P_{max}(t) \tag{2b}$$

where $\dot{m}_f$ is the fuel mass flow rate $[kg/s]$, P is the vehicle power $[kW]$, P_{min} and P_{max} are the minimum and maximum of vehicle power, respectively $[kW]$.

Vehicle power (P) is the control variable of the problem. The optimal solution is the control that minimizes the objective function. The optimal power is achieved when the total trip fuel consumption ($\int_0^{t_e} \dot{m}_f(P(t))dt$) is at its minimum. If $\dot{m}_f$ is independent of P, the objective function would be a linear function of vehicle power and produces a bang-bang control, implying that a driver would have to accelerate at "full throttle (P_{max})" to reduce the time spent accelerating in order to minimize the trip fuel consumption, which is not correct. Consequently, a higher-order model is needed to circumvent this bang-bang type of control.

3. Model Structure

The proposed HDDT fuel consumption model is developed using a framework that is very similar to that of other models within the VT-CPFM program. As a power-based model, the VT-CPFM framework uses a bottom-up approach. Namely, the model parameters, including the resistance forces used for power estimation are first computed using a resistance force module; and thereafter the vehicle power is estimated using an engine power module that characterizes the vehicle power as a function of the resistance forces. The fuel consumption is finally predicted using a fuel rate module that models the fuel consumption as a polynomial function of the vehicle power.

3.1. Resistance Force Module

The resistance force is computed considering a combination of aerodynamic, rolling, and grade resistance forces, as expressed in Eq.(3):

$$R(t) = \frac{\rho_a}{25.92} C_d C_h A_f v(t)^2 + 9.8066m \frac{C_r}{1000}(c_1 v(t) + c_2) + 9.8066mG(t) \tag{3}$$

Here $R(t)$ is the vehicle resistance force (N); ρ_a is the air density at sea level at a temperature of 15 °C (59 °F) (equal to 1.2256 kg/m^3); C_d is the drag coefficient (unitless) which is determined by truck type, 0.78 is used for the tested trucks (no aerodynamic aids) in this study (Rakha et al. (2001)); C_h is the correction factor for altitude (unitless), calculated by 1-0.085H (H is the altitude in km); A_f is the frontal area of trucks (m^2), 10.0 m^2 is used based on the truck type; $v(t)$ is the velocity in km/h; m is the vehicle mass in kg; C_r, c_1 and c_2 are the rolling resistance parameters (unitless), which vary as a function of road surface type and conditions as well as vehicle tire type; their typical values could be obtained from Rakha et al. (2001); Fitch (1994). $G(t)$ is the instantaneous road grade which is determined by elevation profiles.

3.2. Vehicle Power Module

The power exerted at any instant t is formulated by Wong (2001) as expressed in Eq. (4):

$$P(t) = \left(\frac{R(t) + (1 + \lambda + 0.0025\xi v(t)^2)ma(t)}{3600\eta} \right) v(t) \tag{4}$$

where $P(t)$ is the vehicle power in kW; λ is the mass factor accounting for rotational masses, a value of 0.1 is used for heavy duty vehicles (HDVs)(Feng (2007); Edwardes and Rakha (2014)); ξ is the gear ratio and assumed to be zero in this paper due to the lack of engine gear data. $a(t)$ is the instantaneous acceleration (m/s^2); η is the driveline efficiency.

3.3. Fuel Consumption Module

As illustrated in Fig. 1, HDDTs present similar fuel consumption behavior compared to transit buses (as seen in Wang and Rakha (2016a)) with the fuel consumption rate a concave function of vehicle power for the positive powers, and almost constant for the

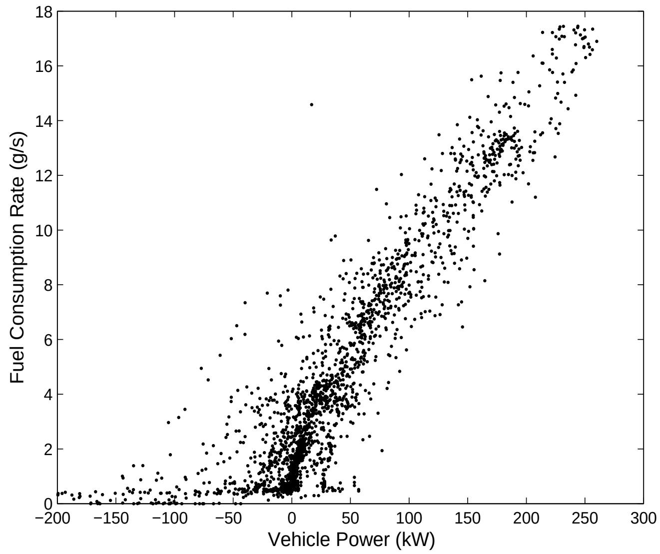


Fig. 1: Vehicle power vs. Truck fuel consumption functional form

negative conditions. Consequently, the general structure of the model is modeled as a two-regime model. Rakha et al. (2011) developed two VT-CPFM frameworks (VT-CPFM-1 and VT-CPFM-2) for LDVs each of which is a two-regime model and characterizes fuel consumption as a second-order polynomial function of vehicle power. The use of a second-order model ensures that a bang-bang control does not result from the application of the model. Furthermore, a model higher than a second-order model cannot be calibrated using standard drive cycles given the complexity of the higher order model. Consequently, a second-order model achieves a good trade-off between model accuracy and applicability. Only VT-CPFM-1 is utilized to develop the model in this study given that VT-CPFM-2 requires additional gear data which is typically not available. The VT-CPFM-1 framework is expressed in Eq.(5):

$$FC(t) = \begin{cases} \alpha_0 + \alpha_1 P(t) + \alpha_2 P(t)^2, & \forall P(t) \geq 0 \\ \alpha_0, & \forall P(t) < 0 \end{cases} \tag{5}$$

Here $FC(t)$ is the fuel consumption rate at instant t [l/s]; α_0, α_1 and α_2 are the vehicle-specific model coefficients that remain to be calibrated.

3.4. Discussion of Model Calibration

It should be noted that the model coefficients, α_0, α_1, and α_2, can be calibrated using publicly available data using Eq.(6)-(8):

$$\alpha_0 = \frac{P_{fmp}\omega_{idle}d}{22164(HV)N} \tag{6}$$

$$\alpha_2 = \frac{(F_{city} - F_{hwy}\frac{P_{city}}{P_{hwy}}) - (T_{city} - T_{hwy}\frac{P_{city}}{P_{hwy}})\alpha_0}{P^2_{city} - P^2_{hwy}\frac{P_{city}}{P_{hwy}}} \tag{7}$$

$$\alpha_1 = \frac{F_{hwy} - T_{hwy}\alpha_0 - P^2_{hwy}\alpha_2}{P_{hwy}} \tag{8}$$

Here P_{fmp} is the idling fuel mean pressure (400,000 Pa); d is the engine displacement (liters); HV is the fuel lower heating value (43,200,000 J/kg for conventional diesel fuel); N is the number of engine cylinders; ω_{idle} is the engine idling speed (rpm); F_{city} and F_{hwy} $(liters)$ are the fuel consumed for the EPA city and highway drive cycles; P_{city}, P^2_{city}, P_{hwy}, P^2_{hwy} are the sum of the power and power squared over the EPA city- and highway-cycle respectively; T_{city} and T_{hwy} are the duration of EPA city and highway drive cycles (s). Most of the parameters typically correspond to either physical characteristics of the vehicles or fuel type, so that they are stated as specifications by the vehicle manufacturer and readily available. Nonetheless, the truck standard driving cycle and the relevant fuel economy data cannot be obtained at this time. Consequently, instead of using publicly available data, the HDDT model is calibrated using second-by-second empirical data.

4. Data Preparation

The data used for model development were collected and provided by the University of California (UC) at Riverside.

4.1. Vehicle Recruitment

The modeling effort is aimed to test the applicability of the VT-CPFM framework to modeling the HDDTs within diverse vehicle-technology categories. Consequently, the recruited trucks should differ in a wide range of vehicle-specific parameters. To this end, a total of eight trucks were randomly recruited from used vehicle fleets in Southern California within test categories by vehicle model year and engine model/displacement, and a balance between horse power and manufacturers was attempted. The detailed vehicle information is presented in Table 1. For simplicity, the eight vehicles, from the top to the bottom of Table 1 are labeled as HDDT1, HDDT2, HDDT3, HDDT4, HDDT5, HDDT6, HDDT7, HDDT8 in the following sections.

4.2. Data Set

Given that in-laboratory data (i.e. chassis dynamometer testing) are not always reflective of real-world driving conditions, on-road data were gathered instead.

To adequately measure real-world fuel consumption and emission levels, UC Riverside developed a mobile emissions research laboratory (MERL) that contains all instrumentation that is normally found in a regular vehicle emission laboratory. MERL weighs approximately 45,000 lbs and could serve as a truck load, so that it is capable of capturing the transient fuel consumption and emissions of a truck pulling it when the truck is being tested. Further details of MERL can be found in Barth et al. (2004); Cocker et al. (2004).

The HDDT test was conducted by the Center for Environmental Research and Technology at UC Riverside on the roadways in California's Coachella Valley involving long, uninterrupted stretches of road, approximately at sea level. All trucks were tested using standard fuel from the same source. The data were recorded at a frequency of 1 Hz and a total of 238,893 seconds of data were gathered with a collection of 8 parameters for each truck, including CO_2, carbon monoxide (CO), hydrocarbon (HC), nitrogen oxides (NO_x), velocity, fuel rate, engine speed and elevation. For more details on data collection procedure, the reader is encouraged to read Barth et al. (2004). It should be noted that the primary goal of this paper is to model the fuel consumption and GHG emissions (CO_2), so that modeling CO, HC and NO_x emissions is out of the scope of this research effort.

4.3. Data Post-processing

The raw fuel consumption rates were in g/s and then converted to l/s in order to use the VT-CPFM framework to develop the proposed model. Simultaneously, the unit of velocity was converted from mi/h to km/h for modeling purposes.

Through comparing the second-by-second CO_2 emissions with engine control unit (ECU) data (i.e. velocity, fuel rate and engine speed), a time delay was found to exist. Consequently, a time alignment was needed to synchronize the raw data. Since fuel rates have a strong relationship with emissions, they were utilized to determine the value of the required time shift. The proper time shift was determined through a cross-correlation analysis by which the correlation coefficients between CO_2 and fuel data were estimated by a correlation function for a range of lag times. The lag times with the highest correlations were selected as the optimal events. It should be noted that the CO_2 emission data collected for two of the trucks (HDDT 4 and HDDT 5) were invalid due to an error in

Table 1: Vehicle-specific information

Make/Model	Model Year	Engine Make/Model	Rated Power (hp)	Engine Size (l)	Vehicle Mass (kg)
International/ 9800 SBA	1997	Cummins/M11-330	330	10.8	7182
Freightliner/ D120	1997	DDC/C-60	360/400	12.7	7758
Freightliner/ D120	1997	Cummins/N14	370/435	14	7029
Freightliner/ C-120	1997	Cummins/N14	370/435	14	7623
Freightliner/ C-120	1998	DDC/C-60	370/430	12.7	8028
Freightliner/ FDL 120	1999	DDC/C-60	470	12.7	8118
Freightliner/ FDL 120	1999	DDC/C-60	360	12.7	8118
Freightliner/FLD 120	2001	CAT/C-15	475	14.6	7092

Table 2: Parameters required for model calibration

Parameter	Value	Source
Drag coefficient (C_d)	0.78	Rakha et al. (2001)
Altitude correction factor (C_h)	NA[a]	Computed from field data
Vehicle frontal area (A_f)	10.0 m^2	Computed from truck dimensions
Vehicle speed (v)	NA[a]	Measured in field
Mass (m)	NA[a]	Manufacturer website
Rolling coefficient (C_r)	1.25	Rakha et al. (2001)
c_1	0.0328	Rakha et al. (2001)
c_2	4.575	Rakha et al. (2001)
Road grade (G)	NA[a]	Computed from field data
Acceleration (a)	NA[a]	Computed from field data
Driveline efficiency (η)	0.94	Rakha et al. (2001)

[a] The parameter is not a single value.

the emission sensors of MERL during the collection process, and thus the model does not covered these vehicles.

The aligned data was smoothed by a moving average filter, and outliers were identified using a cook's distance procedure.

5. Model Development

Each tested truck was individually modeled. Table 2 gives a generalization of the model inputs along with their sources. Some of the variables are capable of being gathered in the field (e.g. vehicle speed), and some can be obtained from either the literature or manufacturer websites (e.g. drag coefficient, vehicle mass).

5.1. Model Calibration Challenges

The model was calibrated using general linear regression analysis, and model coefficients are summarized in Table 3. Unlike LDVs, the second-order parameters (α_2) are negative, which demonstrates that fuel consumption varies as a concave polynomial function of vehicle power and exhibits a mild growth when vehicle power is increasing. This is similar to transit buses in Wang and Rakha (2016a,b) in which the concave model was demonstrated to accurately predict fuel consumption levels.

Nonetheless, the concave model may produce unrealistic driving recommendations as demonstrated by the sensitivity of estimated optimum fuel economy cruise speed to road grade and vehicle weight, as illustrated in Fig. 2 and Fig. 3, respectively. The road grade

Table 3: The concave model for each truck

Truck classification	α_0	α_1	α_2
HDDT 1	1.13E-03	1.11E-04	-1.71E-07
HDDT 2	1.88E-03	1.01E-04	-1.27E-07
HDDT 3	1.56E-03	1.09E-04	-1.24E-07
HDDT 4	1.42E-03	1.03E-04	-1.22E-07
HDDT 5	1.38E-03	1.10E-04	-1.64E-07
HDDT 6	1.02E-03	1.06E-04	-9.28E-08
HDDT 7	9.18E-04	1.06E-04	-8.75E-08
HDDT 8	2.02E-03	8.78E-05	-3.33E-08

varies from -8% to 8% with a span of 2%, and the vehicle weight varies from 17,000 kg to 38,000 kg by having a identical span of 1000 kg. Fig. 2 characterizes the variation of fuel consumption levels over cruise speed at different grade levels, which produces counter intuitive fuel consumption levels, especially when the road grade is high. This implies that the optimum fuel economy cruise speed may increase with the rise of road grade. Fig. 3 also gives unrealistic results that heavier vehicles have higher optimum cruise speeds, implying that, drivers of heavier vehicles, compared to those driving lighter vehicles, are recommended to achieve higher cruise speed to minimize their fuel consumption levels. This is obviously not correct in reality.

Given that the concave model generates a mild increase of fuel consumption with the growth of vehicle power, the unrealistic driving recommendations cannot be avoidable.

5.2. *Model Enhancement*

Given the deficiency of the concave model, an enhancement was considered to make the model more realistic. The convex model had been developed for LDVs and validated to be capable of generating reasonable driving instructions in existing eco-driving and eco-routing systems (Ahn et al. (2011); Park et al. (2011); Rakha et al. (2012)). Consequently, the model was alternatively developed by ensuring that the second-order parameter is positive (linear model has not been considered given that it produces a bang-bang control).

5.2.1. *Convex Model*

To develop a convex model, the order of magnitude of the second-order parameter, which impacts the degree of convexity of the function, needs to be determined. Basically, a lower order of magnitude generates estimates of the convex model less consistent with

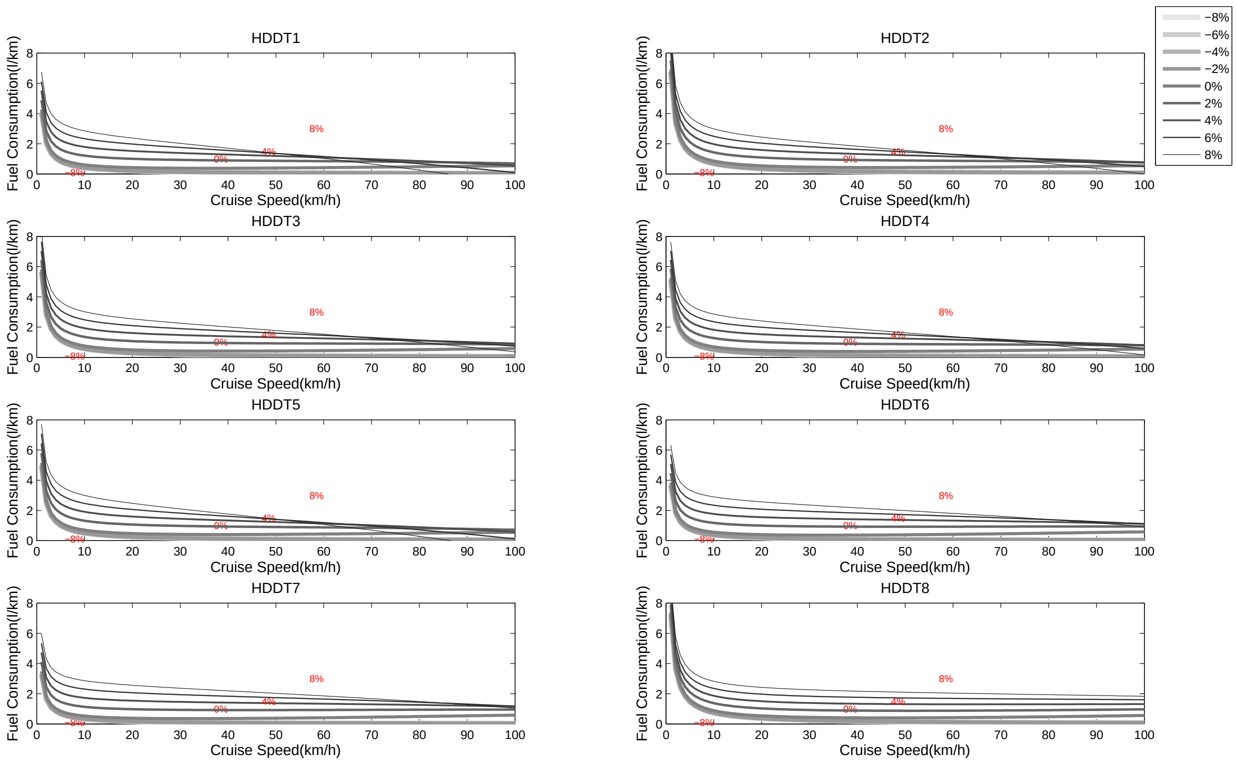


Fig. 2: Fuel consumption levels vs. cruise speed at different grade levels (concave model)

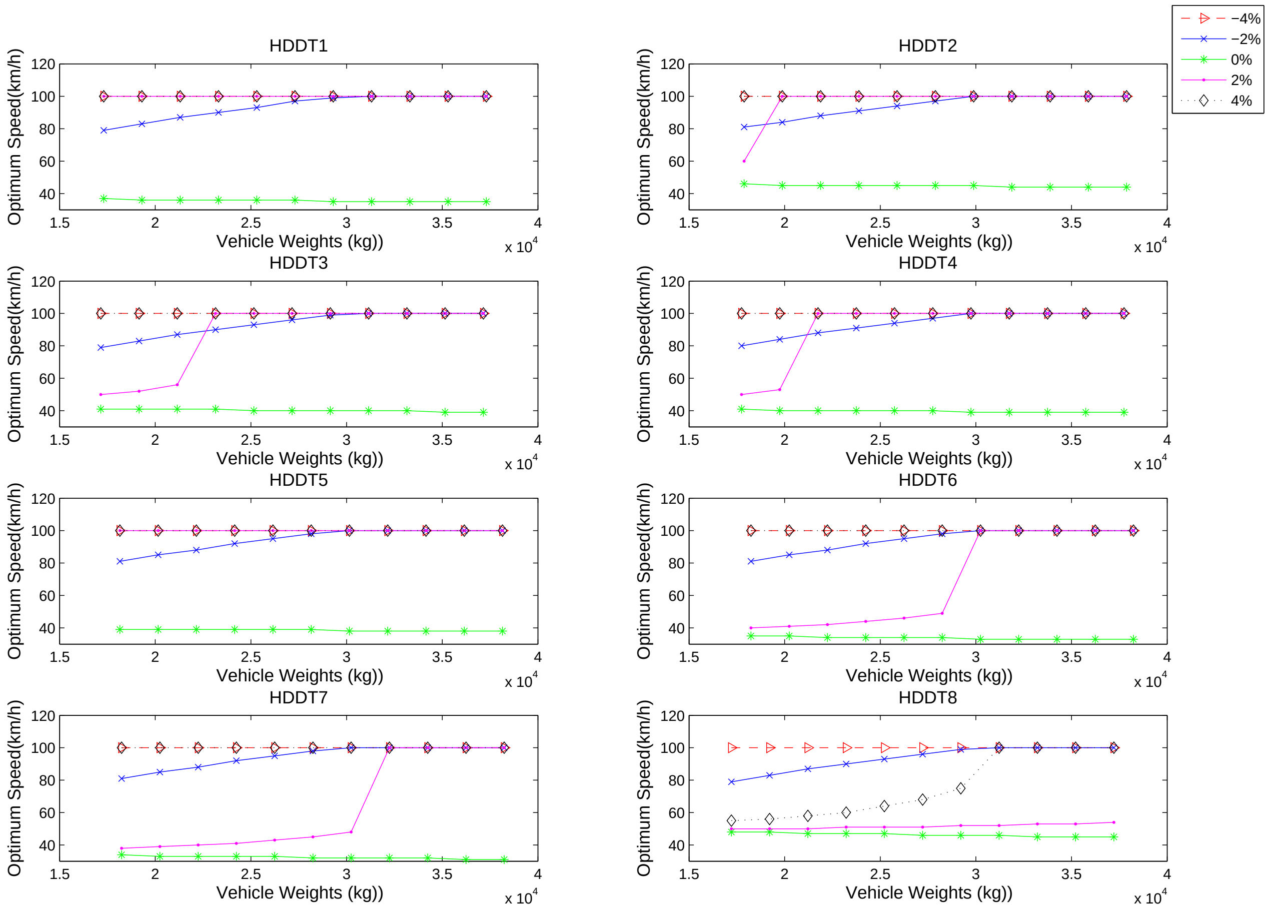


Fig. 3: Impacts of vehicle weight on the optimum fuel economy cruise speed at different grade levels (concave model)

Table 4: The convex model for each truck

Truck classification	α_0	α_1	α_2
HDDT 1	1.56E-03	8.10E-05	1.00E-08
HDDT 2	2.48E-03	7.14E-05	1.00E-08
HDDT 3	2.26E-03	7.82E-05	1.00E-08
HDDT 4	1.80E-03	7.96E-05	1.00E-08
HDDT 5	2.02E-03	7.59E-05	1.00E-08
HDDT 6	1.45E-03	8.48E-05	1.00E-08
HDDT 7	1.31E-03	8.63E-05	1.00E-08
HDDT 8	2.16E-03	7.98E-05	1.00E-08

those of the concave model. Nonetheless, a higher order of magnitude, although more accurate, is very similar to a linear model. A trade-off is thus needed between the accuracy of the model and the degree of convexity. The performance of the convex model in terms of R^2 values has been comprehensively investigated by varying the order of magnitude from $1E-05$ to $1E-11$, as illustrated in Fig. 4. For each model, the R^2 value increases with the growth of the order of magnitude, while the performance achieves little improvement when the coefficient is higher than $1E-08$. Consequently, $1E-08$ was considered as the best order of magnitude in balancing the model performance and the degree of convexity of the model. The convex model is summarized in Table 4.

5.2.2. Sensitivity Analysis of Convex Model

The effects of road grade and vehicle weight on the optimum fuel economy cruise speed were evaluated for the convex model using the same method in section 5.1. As illustrated in Fig. 5, the model produces a bowl-shaped curve as a function of cruise speed and higher road grades result in higher fuel consumption levels, which is similar to LDVs. Specifically, Fig. 6 reveals that, when moving downhill, high cruise speeds can minimize fuel consumption levels, yet not recommended for safety purposes. For uphill, steeper roads result in lower optimum cruise speeds, implying that drivers have to reduce their cruise speed to minimize their fuel consumption levels with an increase in the roadway grade.

Heavier vehicles, as demonstrated in Fig. 7, have higher optimum cruise speeds when moving downhill while lower when moving uphill. It should be noted that, in Fig. 7a, optimum cruise speeds remain constant with an increase in vehicle weight when the road grade is -8%, -6% and -4%. This is because the sensitivity analysis was performed only

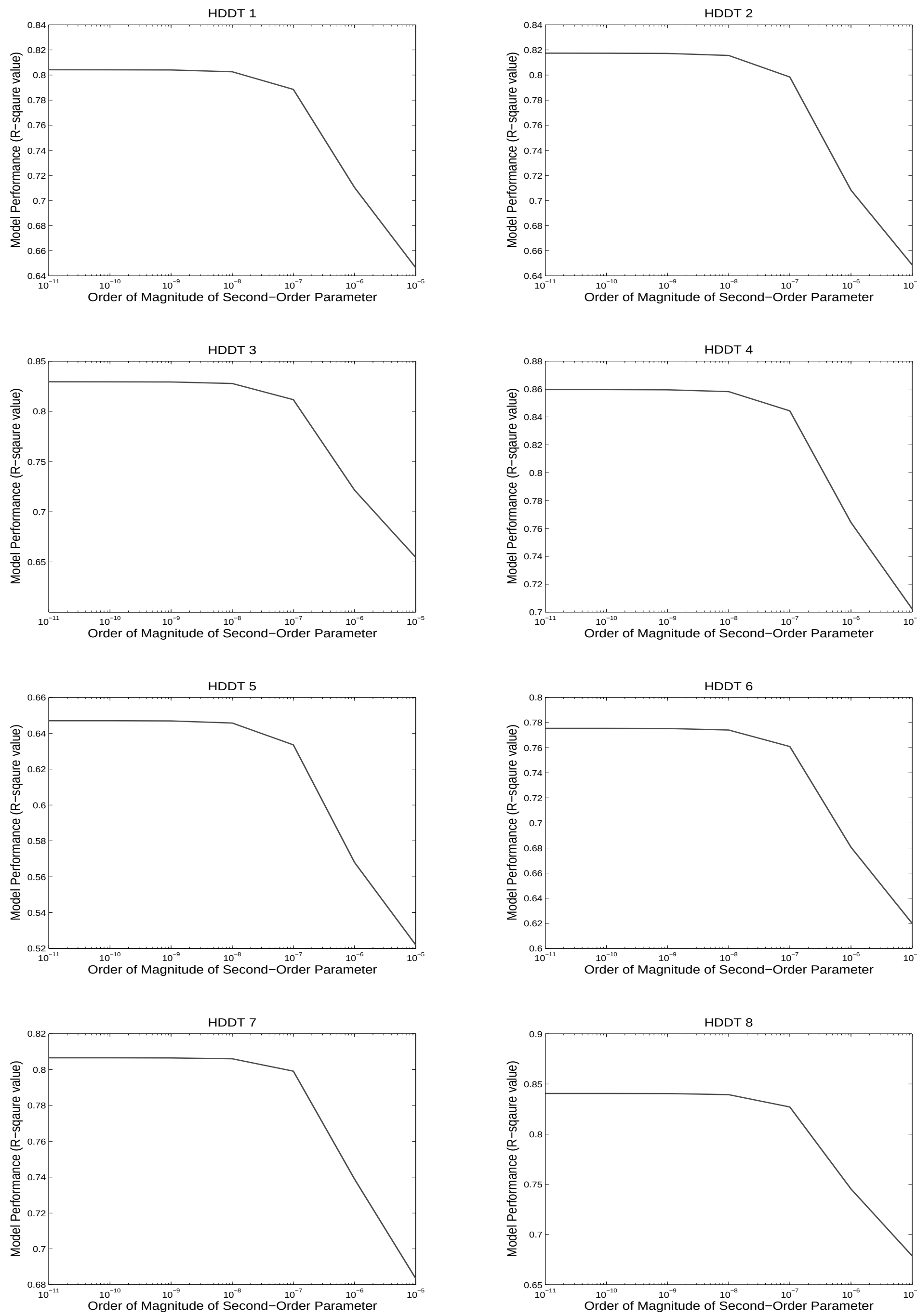


Fig. 4: Model performance vs. order of magnitude of the second-order parameter

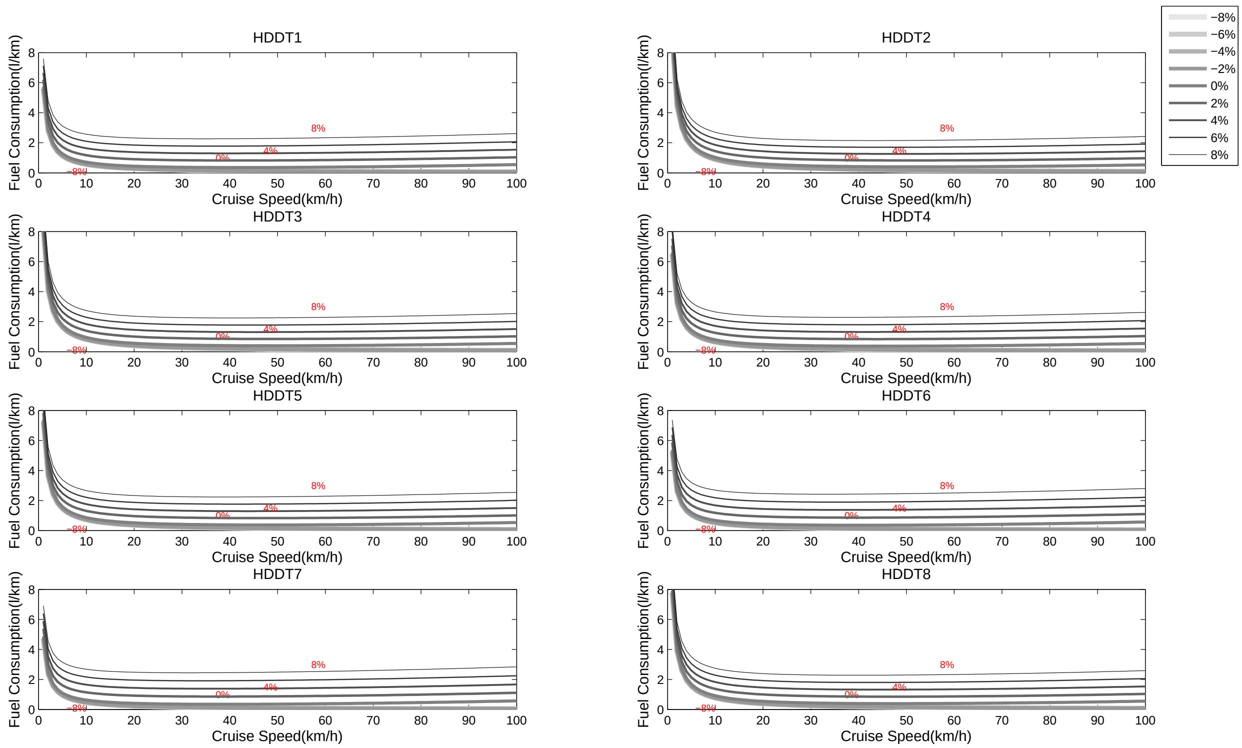


Fig. 5: Fuel consumption levels vs. cruise speed at different grade levels (convex model)

for the speed range of 0-100 km/h and the optimum cruise speeds already reached the maximum level when vehicle weights were at a low level (e.g. 17,000 kg). Furthermore, Fig. 7b clearly indicates that the optimum cruise speeds are more sensitive to vehicle weight at higher grade levels. In short, the convex model can provide reasonable driving recommendations and thus be applicable to eco-driving or eco-routing systems.

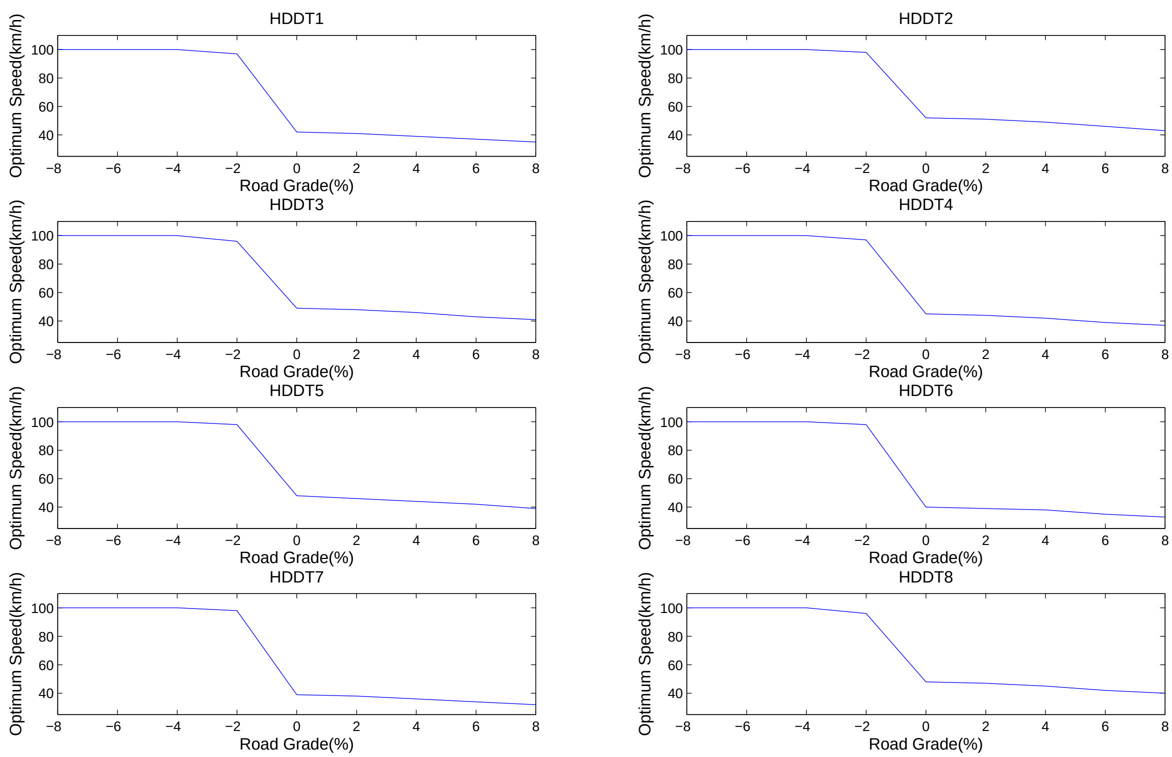
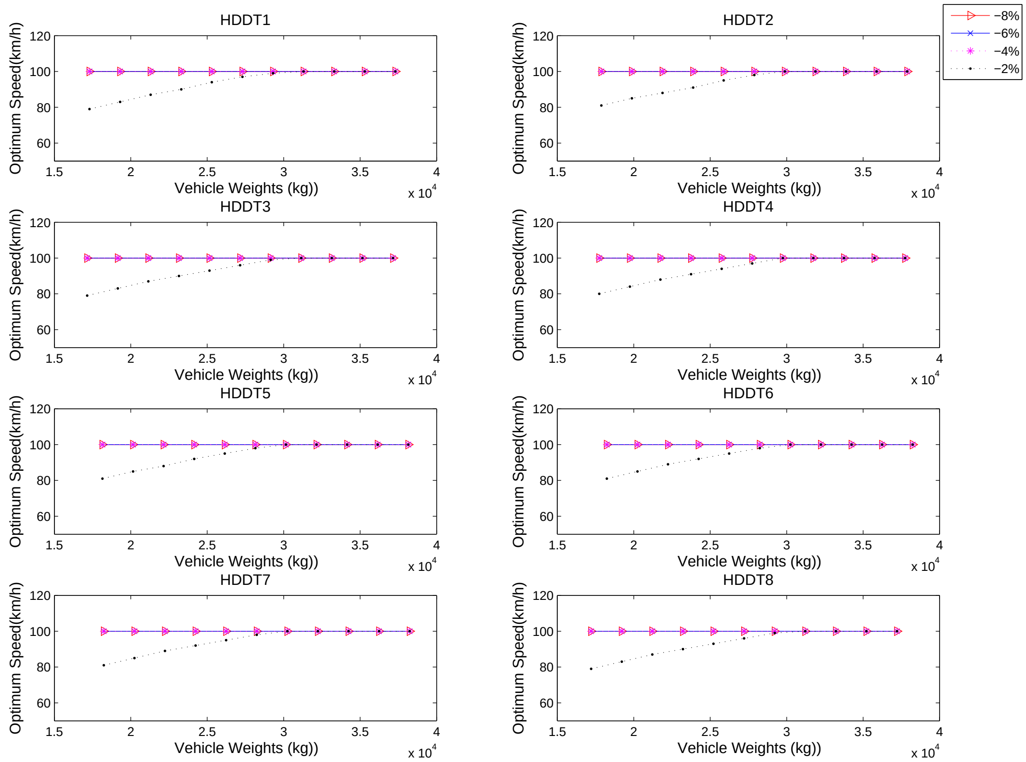
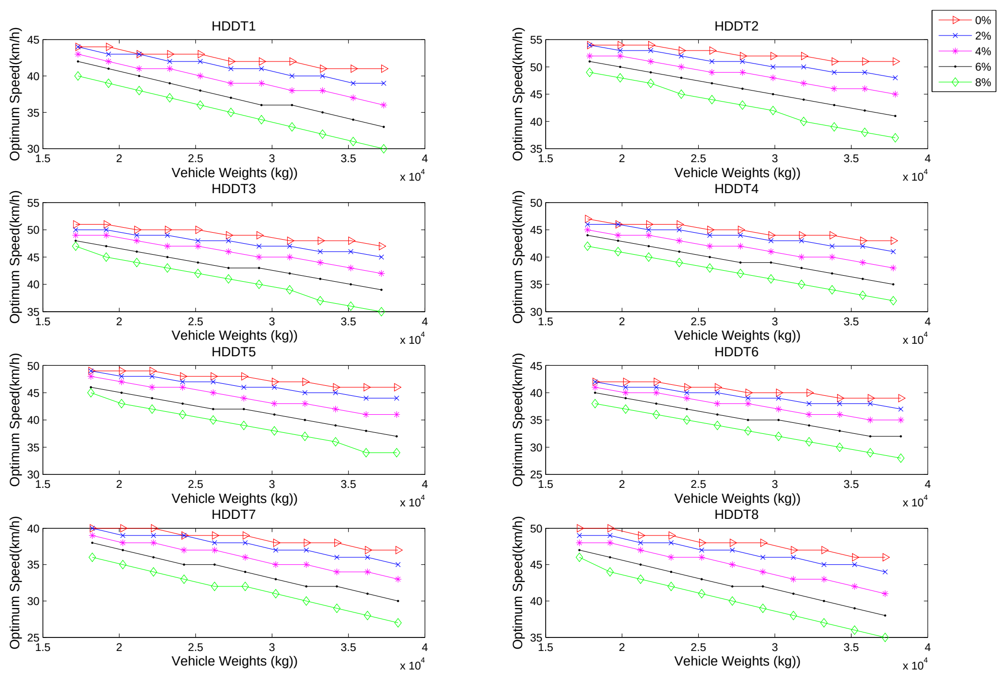


Fig. 6: Impacts of road grade on the optimum fuel economy cruise speed



(a) downhill



(b) uphill

Fig. 7: Impacts of vehicle weight on the optimum fuel economy cruise speed at different grade levels (convex model)

6. Model Validation

A rigorous validation procedure was designed using an independent dataset. The validation process was firstly initiated by comparing the model estimates with field measurements along with CMEM and MOVES estimates at an instantaneous fuel consumption level. Furthermore, the variation of fuel estimates over cruise speed was compared between the proposed model and CMEM. Finally, CO_2 emissions were computed using fuel estimates and validated against in-field measurements.

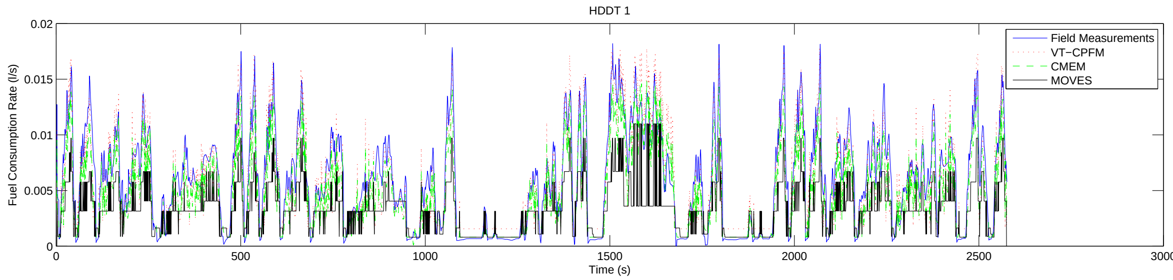
6.1. Instantaneous Fuel Consumption Validation

Fig. 8 provides two example illustrations of the instantaneous model validation, demonstrating that the model estimates in general provide a good agreement with in-field measurements as well as CMEM and MOVES predictions by following the peaks and valleys of the fuel rates. Specifically, Table 5 statistically summarizes the performance of different models. Basically, CMEM performs the best in terms of R^2 values, whereas it produces a bang-bang type of control. Although convex models have a slightly lower R^2 value compared to concave models, they can provide realistic driving recommendations. MOVES performs the worst among the models given that it is designed for conformity use instead of instantaneous analysis; however, it can reflect a large proportion of transient fuel consumption behavior by producing relatively high R^2 values.

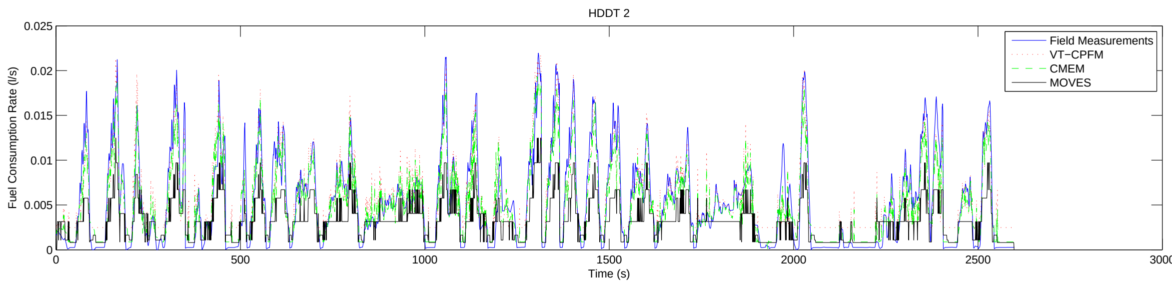
Based on the slopes of the regression lines between model estimates and field measurements, all of the models tend to underestimate the fuel consumption levels with slopes smaller than 1.0, whereas the VT-CPFM model produces better approximation to measurements with higher slope values. MOVES has extremely low slope values given that the MOVES database has no trucks as heavy as the combination of the test truck plus the MERL trailer. The researchers at UC Riverside used MERL to collect data which was accounted for as part of truck load, which makes the total truck load extremely high.

6.2. Optimum Cruise Speed

In validating the proposed model, the variation of fuel predictions over cruise speed was compared against CMEM estimates, as illustrated in Fig. 9 which gives one example result. The two models have highly consistent bowl shaped curves as a function of cruise speed, demonstrating that the proposed model can produce robust fuel estimates. Specifically, the optimum cruise speed ranges between 32∼52 km/h (lower than LDVs: 60∼80 km/h) for all of the test trucks varying the grade level from 0% to 8%, and moves towards the negative direction with the increase of vehicle load and grade level.



(a) HDDT1



(b) HDDT2

Fig. 8: Instantaneous model validation

Table 5: Comparison of model performance

Truck classification	VT-CPFM (concave)		VT-CPFM (convex)		CMEM		MOVES	
	R^2	Slope	R^2	Slope	R^2	Slope	R^2	Slope
HDDT 1	0.82	0.93	0.80	0.87	0.87	0.78	0.72	0.42
HDDT 2	0.83	0.81	0.81	0.76	0.87	0.75	0.76	0.39
HDDT 3	0.84	0.92	0.83	0.81	0.90	0.78	0.77	0.42
HDDT 4	0.87	0.91	0.86	0.88	0.90	0.77	0.78	0.42
HDDT 5	0.66	0.75	0.64	0.69	0.71	0.65	0.57	0.39
HDDT 6	0.78	0.89	0.77	0.86	0.83	0.72	0.72	0.38
HDDT 7	0.81	0.82	0.81	0.78	0.85	0.64	0.74	0.35
HDDT 8	0.84	0.86	0.84	0.84	0.89	0.79	0.78	0.43

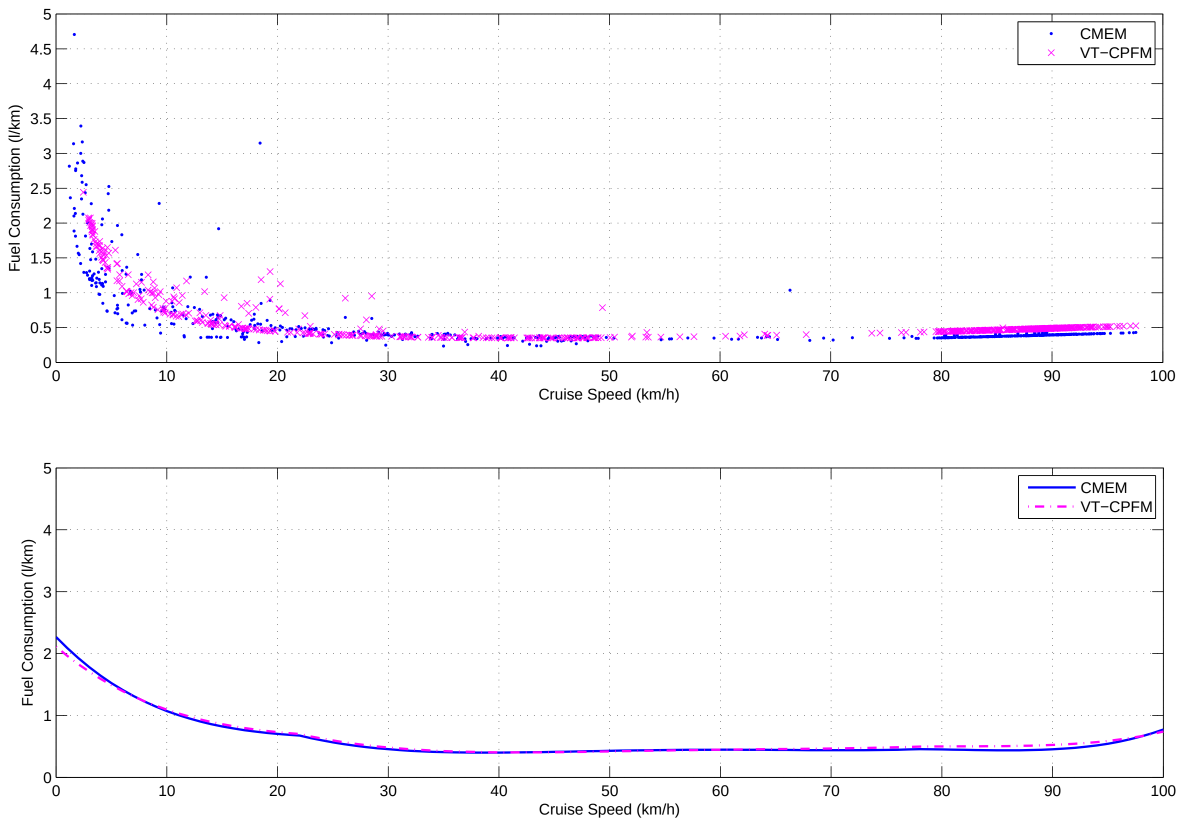


Fig. 9: Impact of cruise speed on fuel consumption levels: VT-CPFM vs. CMEM

Table 6: The performance of CO_2 models

Truck Classification	Coefficients of determination (R^2)	Slope
HDDT 1	0.78	0.95
HDDT 2	0.85	0.72
HDDT 3	0.81	0.82
HDDT 4	NA[a]	NA[a]
HDDT 5	NA[a]	NA[a]
HDDT 6	0.74	0.73
HDDT 7	0.81	0.65
HDDT 8	0.79	0.82

[a] CO_2 model cannot be validated due to the invalid CO_2 in-field measurements.

6.3. CO_2 Emissions

CO_2 can be estimated from the carbon balance equation using the fuel consumption, HC and CO estimates. Given that the magnitude of CO_2 emissions is significantly higher than HC and CO emissions, the fuel consumption level is thus the primary factor that affects CO_2 emissions. As demonstrated in Rakha et al. (2011), CO_2 emission is linearly related to fuel consumption. Eq.(9) was used to capture the relationship between CO_2 and fuel predictions. The model was firstly calibrated for each truck with CO_2 in g/s and fuel consumption in l/s, and the values of θ were then averaged over individual models to generate the average model given that the relationship between CO_2 and fuel consumption is only related to fuel type rather than vehicle type. The value of 2070 was used to compute CO_2 emissions from fuel consumption estimates. It is found that model estimates are in general consistent with field measurements, as the example results illustrated in Fig. 10. The results of other validation efforts are summarized in Table 6 which has an R^2 values ranging between 0.74 and 0.85. In general, the model provides reliable CO_2 predictions. Noticeably, the model cannot be validated for HDDT 4 and HDDT 5 due to a lack of valid CO_2 field measurements, and the model performance is thus not discussed for these vehicles.

$$\theta = \frac{CO_2(t)}{FC(t)} \tag{9}$$

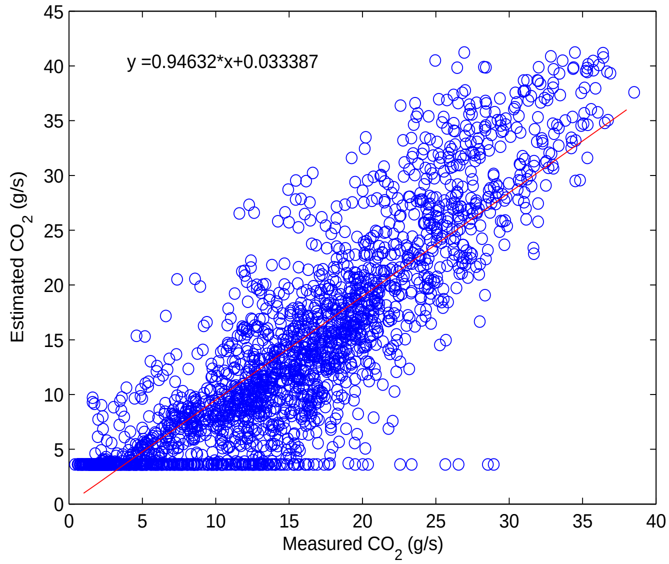


Fig. 10: CO_2 estimation using fuel consumption model (HDDT 1)

7. Conclusions and Recommendations for Further Research

The model developed in this paper circumvents the bang-bang type of control in the family of HDDT fuel consumption models. Given a lack of publicly available data, field measurements are used for model development. The model is calibrated for each individual truck and validated by comparing model estimates against in-field measurements as well as CMEM and MOVES model predictions.

The results of the study demonstrate that the model should be convex, although empirical fuel consumption do seem to point to a concave function of vehicle power, in order to provide realistic driving recommendations from the system perspective. The convex model is demonstrated to estimate fuel consumption levels consistent with in-field measurements and provides better predictions than the CMEM and MOVES models. The optimum fuel economy cruise speed ranges between 32 and 52 km/h for all of the test vehicles with grade levels ranging from 0% to 8%, and moves towards the negative direction with an increase in the vehicle load and grade level; namely, steeper roads and heavier vehicles result in lower optimum cruise speeds. The model also generates accurate CO_2 predictions that are consistent with field data.

Finally, it is recommended that EPA require HDDT manufacturers report their fuel economy in the future so that the models can be calibrated using publicly available data without mass in-field data collection, which can maximize the cost-effectiveness of model development. Although NHTSA provides new fuel efficiency standards, these standards, however, are designed for each truck class (e.g. class 7, class 8) rather than specific truck models. Fuel consumption behavior may differ for different vehicle models within the same class. Consequently, the models developed based on class-specific fuel efficiency data may not adequately capture fuel behavior of each individual truck model.

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