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Statistical Modeling of Exhaust Emissions from Gasoline Passenger Cars

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Abstract: In this study, an instantaneous vehicle emission model was developed and validated. A group of emission regression functions with vehicle speed and VSP as variables was established using the multiple linear regression method and embedded in the instantaneous emission model to predict vehicle emissions. The inputs of the instantaneous vehicle emission model consist of the driving cycle, vehicle parameters and accessories use, all of which are used to calculate the instantaneous vehicle specific power (VSP). The simulated results of the emission model are second-by-second emission rates, emission factors and fuel consumption over the target driving cycle. The predicted emissions as well as fuel consumption of four passenger cars were very close to the tested emission data, and the prediction errors of emission factors and fuel consumptions were acceptable.

Key words: vehicle emission; regression model; statistical analysis; driving dynamics

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With the rapid increase in vehicle population, toxic vehicle emissions have become a major risk to human health and the environment[1-2]. Therefore, it is very important to investigate motor vehicle emissions and evaluate the impact of vehicle emissions on air quality in order to provide technical support for the government to make emission control policies.

Vehicle emissions are affected by many factors including vehicle model, technology level, mass, fuel type, mileage, vehicle speed, vehicle acceleration, and road gradient, etc[3-6]. The complex features of vehicle emissions and vehicle driving conditions make it necessary to use vehicle emission models to forecast or evaluate the vehicle emissions besides emission test.

Many vehicle emissions models have been developed for predicting vehicle exhaust emissions. the vehicle emission models can be classified into two categories: one is bag emission based model, and the other is instantaneous emission model[7]. Bag emission-based models are developed based on the average emission results over a legislative driving cycle and use correction factors to include additional effects such as vehicle load, gearshift strategy or road slope. For example, MOBILE and COPERT[8] were established on the bag emission data and forecast vehicle exhaust emissions based on vehicle average speed. Therefore, these kinds of emission models are usually used to forecast regional or national level vehicle emission inventories and are not suitable for estimating vehicle emissions under more dynamic driving conditions. Because

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the average vehicle speed statistically flattens the dynamic characteristics of acceleration and deceleration, the estimated emissions based on the average vehicle speed cannot be distinguished between the different emission levels of two driving cycles with same average speed, while having completely different instantaneous characteristics. Therefore, some models correlate vehicle emissions with more dynamic driving events by assigning vehicle driving modes into different acceleration/deceleration levels[9], and transient emission characteristics during the driving cycle will be captured and included in calculating the total amount of emissions and emission factors.

Vehicle specific power (VSP) is an important parameter used to characterize the demand of the vehicle 's instantaneous power output, which equates to the vehicle load composed of rolling resistance, aerodynamic drag, acceleration resistance, and grade resistance, all divided by the vehicle mass. The concept of VSP was first proposed by Jiménez at the Massachusetts Institute of Technology[10], and pointed out that VSP is a more suitable parameter to characterize CO, HC and NO_x emissions compared to speed, acceleration, power or fuel rate. VSP is also adopted by MOVES as its principal parameter used to determine vehicle emissions[11].

The development of vehicle emission models uses different approaches. For the modal emission models based on vehicle speed and acceleration[12], the most convenient method is to establish a speed/acceleration matrix to characterize the vehicle operating conditions. Within each bin of speed and acceleration, a statistical mean value of emission rate is provided for each exhaust component. Some other modal emission models include emission maps as functions of engine load and speed. The real-world vehicle emissions and fuel consumption were investigated using the steady-state engine performance map-based vehicle model. The engine performance map based model is sufficient to predict the vehicle emissions and fuel consumption[13]. However, a problem related to the emission mapping approach is the prediction error caused by averaging emission rates within each bin or at each map grid and filtering out transient data. Moreover, interpolating or extrapolating between the emission map grids will also cause obvious errors. To eliminate these kinds of errors, one method is to establish proper analytical formulas to correlate the emission data with the important variables. For example, CMEM was developed by using highly time-resolved vehicle emission data and adopted a modal emission modelling approach using analytical functions that associate the vehicle emissions with vehicle operation conditions[14].

MOBILE forecasts vehicle emissions based on the average traveling speed and uses emission regression functions, which were built by analyzing numerous emission data from Federal Test Procedure (FTP) bag emission measurements[15]. COPERT also uses linear regression to predict vehicle emissions as functions of average vehicle speed. VERSIT+ consists of statistical models[16], which were constructed by multiple linear regression analysis of the relationship between vehicle emission factors and vehicle related variables and has been used in predicting light-duty vehicle emissions under actual traffic conditions. A power-based vehicle emission model was developed and evaluated for spark ignition vehicles, and a linear regression analysis method was used to relate exhaust emissions and fuel consumption to the vehicle dynamic characteristics[17]. A best-fit regression for biodiesel engine emissions was conducted to statistically investigate the effects of biodiesel percentage in the blended fuel, engine type and model year on the engine regulated exhaust emissions[18].

Nowadays, China's huge number of vehicles causes serious air pollution, especially in some big cities including Beijing, Shanghai and Guangzhou. In order to reduce vehicle emissions, policy makers are not only implementing some emission control policies and legislation to promote low

emission vehicles, but also seeking solutions to the transportation system. For the sake of assessing the effects of these measures on vehicle emissions, extensive vehicle real driving emission (RDE) tests have been conducted. However, RDE tests are costly and time consuming, and RDE results are very sensitive to various factors including individual driving behaviour, vehicle parameters and traffic conditions. Therefore, it is necessary to use vehicle emission models to support the assessment of vehicle emissions and fuel consumption. Unfortunately, until now there has been no mature microscopic vehicle emission model in China. Some researchers in China applied the MOBILE model[19], CMEM model[20], COPERT model[21] or IVE model[22] to estimate vehicle emissions in China with some modifications.

In this paper, an instantaneous vehicle emission model was developed by establishing statistical emission models to predict passenger car emissions. The emission rates of each exhaust component were modelled by analytical formulas using speed and VSP as variables. By using VSP, the effects of vehicle air and rolling resistance, driving dynamics, road gradient and accessories use can be properly taken into account. The statistical formulas for emissions were established by using multiple linear regression method to correlate the instantaneous emission rates with vehicle speed and VSP based on the second-by-second emission data of CO, HC, NO_x and CO_2, which were obtained by testing four passenger cars on chassis dynamometer over several driving cycles. This instantaneous vehicle emission model was proposed for predicting the emission characteristics of passenger cars under different driving conditions. In addition, vehicle fuel consumption was estimated by the carbon balance method. As a result, the passenger car emissions and fuel consumption can be simulated for any driving cycle without the need for vehicle emission testing. The methods and the results are presented below.

1 Experimental Section

1.1 Testing facilities and equipment

Four passenger cars from the same manufacturer were tested on a chassis dynamometer in this paper. Tab. 1 lists their key specifications. They are equipped with a four-stroke, spark ignition (SI) gasoline engine, compliant with the China-5 (equivalent to Euro-5) emission standard with multi-point fuel injection (MPFI) and three-way catalyst (TWC).

Tab. 1 Vehicle specifications

Car No.	Fuel type	Number of cylinders	Engine capacity/L	Maximum power/kW	Kerb weight/kg	Mileage/km	Transmission	Technology
Car A	Gasoline	4	1.78	110.0	1378	3680	Automatic	China-5
Car B	Gasoline	4	1.60	93.8	1233	3000	Automatic	China-5
Car C	Gasoline	4	1.60	93.8	1267	100	Automatic	China-5
Car D	Gasoline	4	1.60	93.8	1267	4000	Automatic	China-5

While testing on the chassis dynamometer, the total driving resistive force of the test vehicle was simulated and exerted by an Ono Sokki PECD-9400 chassis dynamometer. A Horiba MEXA-7200H emission analyser and a CVS7400T sampling system were utilized to measure vehicle exhaust emissions including CO, HC, NO_x and CO_2.

The schematic of the vehicle emission test system is depicted in Fig. 1.

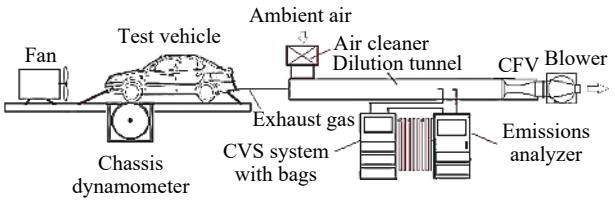


Fig. 1 Schematic of vehicle emission test system

1.2 Test cycles and protocols

Although the vehicle emissions tested on the chassis dynamometer cannot directly reflect the

vehicle real-world driving emissions, testing vehicle emissions in a laboratory is a widely accepted approach for the measurement of vehicle emission due to its high degrees of precision and standardization, which are significant for developing a database of emission models. The emissions of four passenger cars were tested in a laboratory over several vehicle driving cycles including the Federal Test Procedure (FTP) 75, New European Driving Cycle (NEDC) and Beijing Light Duty Test Cycle (BJLTC).

The NEDC driving cycle is mostly used to test the emission levels of light duty vehicles in both Europe and China. It contains four-repeated Urban Driving Cycles (UDC) and one Extra-Urban Driving Cycle (EUDC), which characterizes typical urban driving conditions and extra-urban driving conditions separately. The total duration of the NEDC is 1 180 s, and the total travel distance is 11.007 km with a maximum speed of 120 km·h^{-1}[23].

The FTP75 driving cycle is used by the US Environmental Protection Agency (EPA) to test light duty vehicle emissions and fuel economy. The total FTP75 driving cycle lasts 1874 s and travels 7.77 km with a maximum speed of 91.2 km·h^{-1}.

The Beijing Light Duty Test Cycle (BJLTC) is shown in Fig. 2 and was derived from the database of Beijing light duty vehicle real road driving trips. The total duration of the BJLTC test cycle is 1 153 s, and the total travel distance is 9.7 km with a peak speed of 113.5 km·h^{-1}.

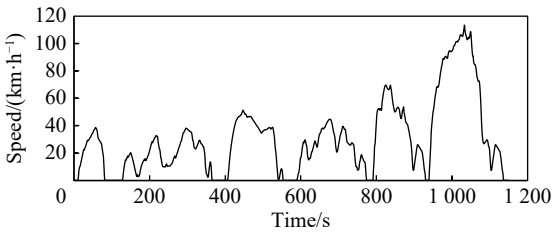


Fig. 2 Beijing Light Duty Test Cycle (BJLTC)

During each emission test, the vehicle exhaust gases were diluted by the ambient air in the CVS system. The partially diluted exhaust gas was sampled and collected in sampling bags during the whole driving cycle for later analysis after the test. In the meantime, a part of the diluted exhaust gas was inducted into the MEXA-7200H emission analyser and measured simultaneously providing the second-by-second emission data for CO, HC, NO_x and CO_2 output over the driving cycle. Based on the measured concentrations of each component of the exhaust in the sample bag, the total diluted gas volume, the density of each component, and the mass emissions of vehicle exhaust pollutants can be calculated.

2 Emission Regression Model Development

The establishment of vehicle emission regression models needs plenty of emission data measured under various vehicle operating conditions. Moreover, for model development, it is necessary to identify some key parameters that play important roles in determining the level of vehicle exhaust emissions. Building the emission regression model encompasses combining the emission model with the key vehicle operating parameters to build correlation functions between the emission data and the characteristic parameters that can act as the inputs of the emission regression model.

The emission variance from one vehicle to another is significant. In this paper, the instantaneous emission model was developed at the vehicle level. After warming up, four passenger cars were tested over NEDC, FTP75 and BJLTC driving cycles, and the measured instantaneous emission data was used to develop the emission regression model.

The parameters that characterize vehicle operating conditions include vehicle speed, acceleration, deceleration, engine power, vehicle specific power, road grade and the use of vehicle accessories, etc. Out of these parameters, vehicle speed and VSP have been proved to be two key parameters in determining the vehicle emission

levels. Using VSP, the effects of vehicle driving resistance, driving dynamics, road gradient and the use of accessories can be calculated properly and considered.

VSP was originally defined by Jiménez as the needed instantaneous motive power per unit mass[10], and can be calculated by

$$P_s = v[a(1+\varepsilon_i) + g\sin\theta + \frac{9.806\,65(A+Bv+Cv^2)}{m}] + \frac{P_a}{m} \quad (1)$$

where P_s is VSP ($\mathrm{kW\cdot t^{-1}}$ or $\mathrm{m^2\cdot s^{-3}}$), v is the vehicle speed ($\mathrm{m\cdot s^{-1}}$), a is acceleration ($\mathrm{m\cdot s^{-2}}$), ε_i is the equivalent ratio of the translational mass of the vehicle powertrain rotating components (gears, shafts, wheels, etc.) (a factor of 0.05 is used here), g is the acceleration due to gravity ($\mathrm{m\cdot s^{-2}}$), and θ is the angle of the roadway with the horizontal, A, B, and C are the coast down coefficients representing the combined effects of aerodynamic drag and rolling resistances of the tires, m is vehicle mass in ton, and P_a is the power needed for accessories (such as air-conditioning). Note that the vehicle mass remains in Eq. (1), while the calculation of VSP is still dependent on vehicle mass.

The development of the emission regression model involves relating vehicle emissions to the selected variables. Therefore, a multiple linear regression method was applied to determine the correlation between vehicle emissions and the vehicle speed and VSP. and then include them in the regression models.

The multiple linear regression formula for the emissions estimation of CO, HC, NO_x and CO_2 is predefined as

$$E_i = c_i + \sum a_i v^i + \sum b_i P_s^i \quad (2)$$

where E_i represents the exhaust emission rate of CO, HC, NO_x or CO_2 from the vehicle in g/s respectively, c_i is the constant of the regression formula for each pollutant. a_i is the regression coefficient for variable v^i (here i also specifies the polynomial power of v), and b_i is the regression coefficient for variable P_s.

The dependence of each component's emission rates on the vehicle speed and VSP will be analyzed respectively in the following sections.

We can use the Matlab function "polyfit(x,y,n)" to gain the coefficients of the polynomial $y(x)$ of degree n, which fits the vehicle emission data as a function of speed according to the least squares criteria[24], or use the polynomial fitting method in Excel to determine the coefficients of the polynomial emission formula with vehicle speed as a variable.

2.1 Correlation between vehicle emissions and speed

This section provides insight into the correlation between vehicle emissions and speed. Considering the discrete nature of vehicle emission data, we use the least squares curve fitting method to turn such discrete values into a continuous function to show the correlations between vehicle emissions and vehicle speed. The method of least squares can produce the most probable approximation of the parameters with a minimal deviation from all data points.

Fig. 3 depicts the scattered vehicle emission data and fitted curves of CO, HC, NO_x and CO_2 emission rates.

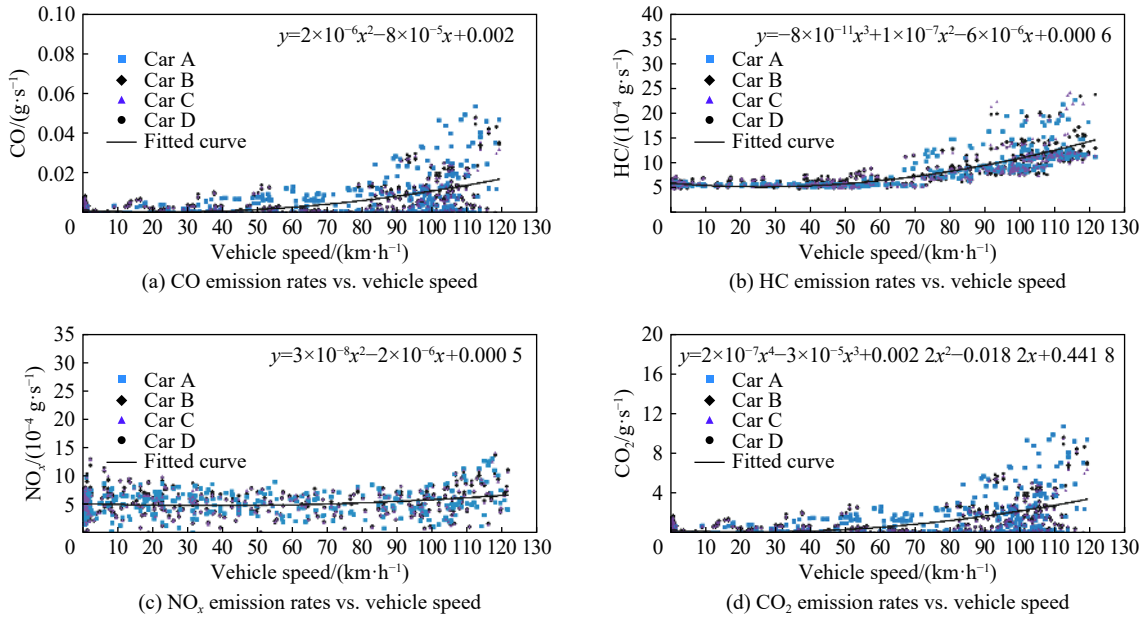
The fitted degree n of the polynomial functions for the CO, HC, NO_x and CO_2 emission data vs. vehicle speed is 2, 3, 2 and 4, respectively. Therefore, we use the following polynomial function to describe each emission pollutant as a function of vehicle speed

$$E_i = a_0 + a_1 v + a_2 v^2 + a_3 v^3 + a_4 v^4 \quad (3)$$

where E_i stands for the vehicle emission rates of CO, HC, NO_x or CO_2 in $\mathrm{g\cdot s^{-1}}$, a_0 is the constant of the regression function for each pollutant. a_i is the regression coefficient for variable v_i (here i specifies the polynomial power of v), and is shown in each figure.

Fig. 3a– 3d show the relationships between the emission rates of CO, HC, NO_x and CO_2 and vehicle speed fitted using the 2nd, 3rd, 2nd and 4th order polynomial respectively. Vehicle emission rates of CO, HC, NO_x and CO_2 vary signific-

antly with vehicle speed. The increased air resistance at high vehicle speed requires higher engine output power, which leads to the increased emission rates of CO, HC and CO_2, most likely the engine goes into an enrichment regime at high engine load. NO_x emission rates increase slightly when vehicle speed exceeds 80 km/h, but smoother compared with that of CO and HC when the engine operates at enrichment conditions, which will deter the formation of NO_x. As expected, the CO_2 emission rates increase with the engine output power when the vehicle speed increases, since the amount of CO_2 emission relates strongly to engine load and fuel consumption.



(a) CO emission rates vs. vehicle speed
(b) HC emission rates vs. vehicle speed
(c) NO_x emission rates vs. vehicle speed
(d) CO_2 emission rates vs. vehicle speed

Fig. 3 Scattered emission data and fitted curves for CO, HC, NO_x and CO_2 emission rates

2.2 Correlation between vehicle emissions and VSP

VSP can also be used as a variable to characterize vehicle exhaust emissions regardless of the vehicle's physical parameters, such as vehicle weight, type, engine size, etc.

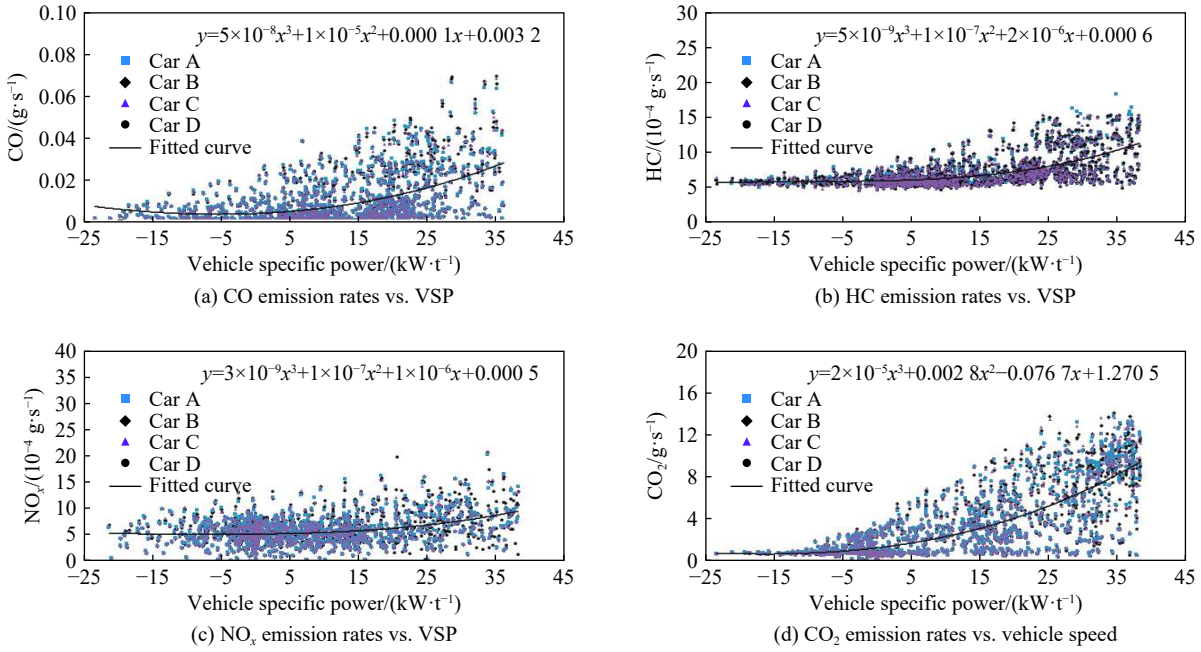
The relationships between vehicle emissions and VSP were studied to investigate the effects of VSP on the vehicle emissions. The plots of vehicle emission rates against VSP are presented in Fig. 4.

The highest degree n of the polynomial functions for the CO, HC, $NO_x$and CO_2 emission data vs. VSP is three. Therefore, we use the following polynomial function to describe the relationship between each emission pollutant and VSP

$$E_i = b_0 + b_1 P_s + b_2 P_s^2 + b_3 P_s^3 \qquad (4)$$

where E_i stands for vehicle emission rates of CO, HC, NO_x or CO_2 from the vehicle in g/s respectively, b_0 is the constant in the regression formula for each pollutant. b_i is the regression coefficient for variable P_s^i (here i specifies the polynomial power of P_s), shown in Fig. 4.

Fig. 4a– 4d show the relationships between VSP and the emission rates of CO, HC, NO_x and CO_2, which can be fitted using 3rd order polynomial curves. In the negative VSP section, the vehicle emission rates of CO, HC, NO_x and CO_2 are low due to the engine operating at an idle state or forced idling. While in the positive VSP zone, the emission rates of CO, HC, NO_x and CO_2 increase with engine output power, especially CO output. With the increased VSP, the engine load rises close to full load and operates on a rich air fuel mixture that will lead to a rapid increase in CO emissions.



(a) CO emission rates vs. VSP (b) HC emission rates vs. VSP

(c) NO_x emission rates vs. VSP (d) CO_2 emission rates vs. vehicle speed

Fig. 4 Scattered emission data and fitted curves for CO, HC, NO_x and CO_2 emissions

2.3 Emission regression model as functions of vehicle speed and VSP

Based on the dependence of vehicle emission rates on speed and VSP, we predefine the regression function of the vehicle emission rates with vehicle speed and VSP as variables in the following equation as

$$E_i = c_0 + a_1 v + a_2 v^2 + a_3 v^3 + a_4 v^4 + b_1 P_s + b_2 P_s^2 + b_3 P_s^3 \quad (5)$$

where E_i stands for the emission rates of CO, HC, NO_x or CO_2 from the vehicle in $mg \cdot s^{-1}$, $mg \cdot s^{-1}$, $mg \cdot s^{-1}$ and $g \cdot s^{-1}$ respectively. We calculate the regression coefficients and constants of the function of each component emission rates associated with vehicle speed and VSP with the Matlab function[24]

$$[b, \text{bint}, r, \text{rint}, \text{stats}] = \text{regress}(y, X, \alpha) \quad (6)$$

where b is the coefficient vector estimated by linear regression of the response variable y (here y represents E_i, which is an n-by-1 vector) against the predictors in the X matrix, which includes a column of 1s in order to obtain a constant term. The statistics provided include the R^2 value, F statistic, p value, and the estimate of error variance. The F statistic is the value resulting from performing the F-test on the regression model. The α value represents a parameter in the regression function using a $100(1-\alpha)\%$ confidence level to compute bint and rint, here the assigned value of α is 0.05.

In this paper, in order to ensure a strong correlation between the scattered raw data and fitted values, for P value test method, the P value should be less than α,and the R^2 value larger than 0.6. The coefficients obtained from the multiple linear regressions of the CO, HC, NO_x, and CO_2 emission rates as functions of vehicle speed and VSP are shown in Tab. 2.

The emission regression model consists mainly of the above regression functions of emission rates using vehicle speed and VSP as variables, which act as the core model of the vehicle instantaneous emission model described in Fig.5. The vehicle instantaneous emission model is used to simulate the vehicle exhaust emissions under various driving conditions. Therefore, the emission rates and emission factors of each exhaust component can be calculated over the selected driving cycle.

Tab. 2 Coefficients and constants of the multiple linear regressions of the emission rates

Emission rate/(g·s^{-1})		CO/(mg·s^{-1})	HC/(mg·s^{-1})	NO$_x$/(mg·s^{-1})	CO$_2$/(g·s^{-1})
Regression coefficients	c_0	1.672	0.559	0.499	0.39
	a1	–0.541	1.12×10^{-3}	6.93×10^{-3}	0.0391
	a2	0.048	-1.31×10^{-5}	-1.70×10^{-4}	2.73×10^{-3}
	a3	-1.08×10^{-3}	-3.62×10^{-7}	1.24×10^{-6}	3.00×10^{-6}
	a4	0	6.39×10^{-9}	0	-6.24×10^{-8}
	b1	0.383	5.93×10^{-4}	–0.0095	0.198
	b2	0.066	1.24×10^{-3}	1.89×10^{-7}	2.20×10^{-3}
	b3	3.81×10^{-8}	3.23×10^{-5}	8.28×10^{-9}	5.12×10^{-8}

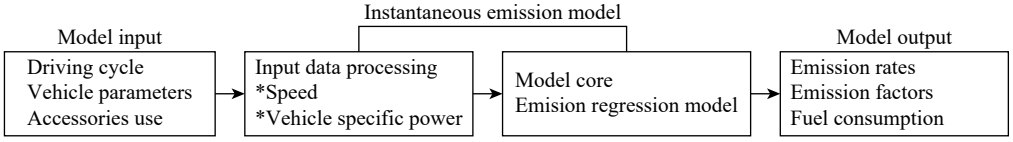


Fig. 5 Schematic of the instantaneous emission model

The model inputs consist of a driving cycle (usually represented as a speed-time profile), vehicle parameters and accessories use (air-conditioning, etc). The vehicle instantaneous speed is derived from the input driving cycle, then the acceleration is calculated as the rate of change in speed. Accordingly, the instantaneous VSP is calculated via Eq. (1). Furthermore, based on Eq. (5), denoting the emission regression statistical and the respective regression coefficients and constants associated with vehicle speed and VSP for vehicle emissions estimation in Tab. 2, the instantaneous emission rates of CO, HC, NO_x, and CO_2 over the selected driving cycle can be calculated. Then, the emission factor of each emission component can be calculated by

$$f_e = \frac{\sum m_{et} \cdot \Delta t}{\sum v_t \cdot \Delta t} \tag{7}$$

where f_e is the emission factor in g/km, m_{et} is the mass emission rate of each component at time t, v_t is vehicle speed at time t, and Δt is the simulation time step.

The vehicle fuel consumption is calculated using the carbon balance method[25]. For a vehicle equipped with a gasoline engine, its fuel consumption is calculated by

$$F_C = (0.1154/D)\,(0.866E_{HC} + 0.429E_{CO} + 0.273E_{CO_2}) \tag{8}$$

where F_C is the vehicle fuel consumption per 100 km in liters. E_{HC}, E_{CO} and E_{CO_2} are the emission factors of HC, CO and CO_2 in g/km respectively, and D is gasoline density at 15 ℃.

The program of the vehicle emission regression model was written in Matlab and can be used to forecast vehicle emissions at both the microscale and macroscale levels. For example, if the vehicle second-by-second speed profile is given, the emission rate from every second of each exhaust component can be calculated. On the other hand, if the typical vehicle driving mode such as average speed is given, the vehicle emissions based on the average vehicle kinematic parameters can also be estimated.

3 Results and Discussion

The instantaneous emission model was developed based on the exhaust emissions of four passenger cars, therefore, the simulated vehicle emissions reflect a fleet average emission level of these four cars. For the purposes of validating the instantaneous emission model, four passenger cars were tested over the hot part of the worldwide harmonized light-duty test cycle (WLTC). The measured emissions of four passenger cars were separately compared with the model-simulated results (Tab. 3). The prediction errors of the emission model for the emis-

sion factors were calculated by

$$E_r(\%) = 100(X - Y)/Y \quad (9)$$

where X and Y are the calculated and tested emission factors of each exhaust component over the WLTC driving cycle, respectively.

Shown in Tab. 3, the exhaust emission factors of these four cars have been found to be different from each other, but all close to the simulated results of the instantaneous emission model, which means that the vehicle instantaneous emission model can predict the emissions of these four cars with acceptable performance. The CO_2 emissions and fuel consumption, in particular, match well for the four cars.

Tab. 3 Comparison of the measured and predicted emissions and fuel consumptions

Car	Type	HC/(g·km^{-1})	CO/(g·km^{-1})	NO_x/(g·km^{-1})	CO_2/(g·km^{-1})	Fuel consumption/(L·(100 km^{-1}))
Car A	Predicted result	0.0594	0.5130	0.0421	141.89	6.10
	Tested result	0.0632	0.5240	0.0412	145.67	6.26
	Error	–6.01%	–2.11%	2.18%	–2.59%	–2.59%
Car B	Predicted result	0.0564	0.5020	0.0420	141.27	6.07
	Tested result	0.0528	0.4790	0.0402	138.25	5.94
	Error	6.75%	4.80%	4.35%	2.18%	2.20%
Car C	Predicted result	0.0587	0.5540	0.0428	138.12	5.94
	Tested result	0.0613	0.5930	0.0453	139.45	6.00
	Error	–4.24%	–6.58%	–5.54%	–0.95%	–1.00%
Car D	Predicted data	0.0582	0.5080	0.0418	139.93	6.02
	Tested data	0.0563	0.4830	0.0404	138.18	5.94
	Error	3.45%	6.21%	4.20%	2.68%	2.71%

The simulated and tested real time emission rates of CO, HC, NO_x, and CO_2 from Car A were compared. Here, the medium and high-speed phases of the WLTC driving cycle were selected as the basis for comparison between the simulated results and the tested data. The reason for choosing this speed time profile is that it more likely represents the real road driving behavior[26]. The low speed part of the WLTC was not selected in order to eliminate the effects of the engine starting. Furthermore, the extra-high speed phase of the WLTC was removed due to its maximum speed of 131.3 km·h^{-1} being much higher than the highway speed limit of 120 km·h^{-1} in China.

Fig. 6 shows the medium and high-speed phase of the WLTC driving cycle. This driving trip is 11.91 km long, lasts 888 s and has an average speed of 48.2 km·h^{-1} with a maximum speed of 97.4 km·h^{-1}.

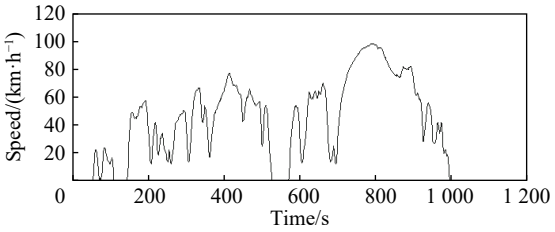
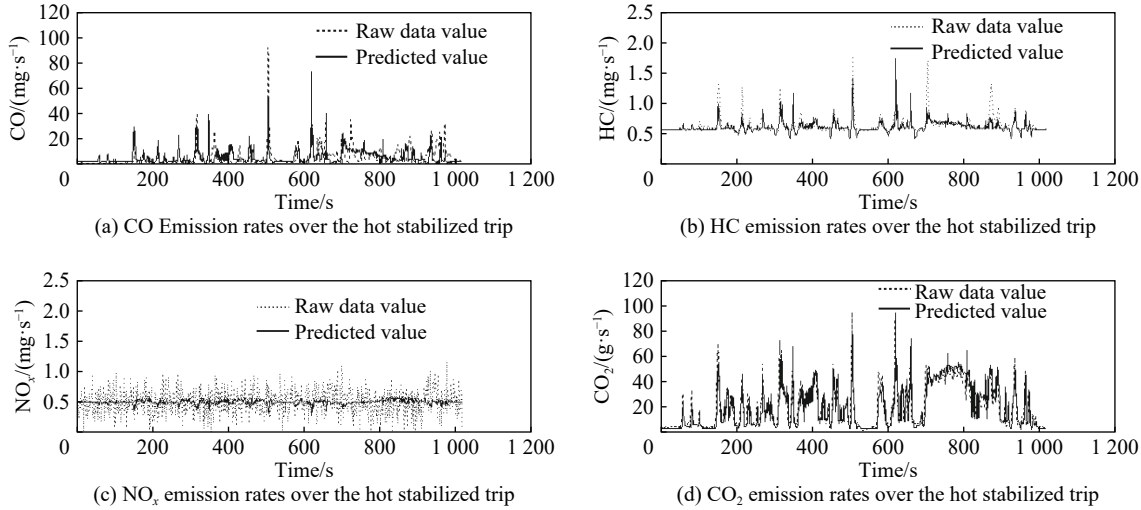


Fig. 6 Speed profile of the selected driving cycle

Using this driving cycle as the input of the emission regression model, the second-by-second emission rates of each exhaust component released from Car A were obtained, and compared with the measured data to validate the regression emission model. The comparisons of the simulated emission rates and the tested emission rates of CO, HC, NO_x and CO_2 emitted from Car A are shown in Fig. 7a–7d, respectively.

Fig. 7a–7d showed that the emission regression model can simulate the real time vehicle emissions under various driving conditions. However, we realize that the calculated emission

rates cannot trace the peaks and valleys of the tested raw data, such as NO_x emission rates, because the calculated emission results represent the statistically averaged values of many tested raw data points at the same vehicle driving mode. Therefore, the big fluctuations of the tested raw data have been partially smoothed while keeping the main topological characteristics of the primary data.



(a) CO Emission rates over the hot stabilized trip

(b) HC emission rates over the hot stabilized trip

(c) NO_x emission rates over the hot stabilized trip

(d) CO_2 emission rates over the hot stabilized trip

Fig. 7 Comparisons of the predicted and the tested emission results of Car A

The method of Pearson correlation coefficient was used to evaluate the linear correlation between the predicted and measured emission rates of CO, HC, NO_x and CO_2 over the selected driving cycle. The Pearson correlation coefficient indicates the strength of association between two variables[27], and is calculated as

$$r = \frac{\sum(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum (x_i - \bar{x})^2 (y_i - \bar{y})^2}} \qquad (10)$$

where x_i and y_i represent the measured and predicted emission rates of CO, HC, NO_x and CO_2, respectively, $\bar{x}$ and $\bar{y}$ are the corresponding mean values to x_i and y_i over the whole trip.

For Car A, the correlation coefficients of the measured and predicted emission rates are 0.81, 0.91, 0.55 and 0.94 for CO, HC, NO_x and CO_2, respectively, and shows that the predicted emission results of this emission model are satisfactory for emission estimation of the passenger car.

The inputs of the emission model also include the parameters of road gradient and accessories use, however in this validation case, they were not included in the selected driving cycle because the vehicle was tested on chassis dynamometer in laboratory. In addition, startup emissions that include cold start and hot start emissions, which were not considered in the core model, are handled with correction factors based on the vehicle driving conditions. In addition, if the emission regression model is aimed to forecast the fleet-averaged emission levels of passenger cars, more tested emission data of other passenger cars need to be incorporated into the emission model.

4 Conclusion

In this study, an instantaneous vehicle emission model, which includes a group of emission regression functions with vehicle speed and VSP as variables, was established for modeling vehicle emissions. The emission data of four passenger cars tested over NEDC, FTP75 and BJLTC driving cycles were utilized in developing the emission regression model. The inputs of this emission model consist of driving cycle (road gradient can also be included), vehicle parameters (mass, coast-down coefficients) and accessories

use (air-conditioning, etc.), all of which were used to calculate the instantaneous VSP. The model outputs are second-by-second emission rates, emission factors and fuel consumption of the selected driving cycle. The calculated emission results of the four cars using the emission regression model were very close to the measured emission data, and the agreements between the predicted and measured real time emission rates for Car A were satisfactory. The results showed that the instantaneous emission model could be applied in estimating the vehicle emissions and fuel-consumption for any driving cycle instead of vehicle testing.

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