Development of Speed Correction Factors Based on Speed-Specific Distributions of Vehicle Specific Power for Urban Restricted-Access Roadways

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Abstract: Precise facility-specific speed correction factors (SCFs) are important parameters for direct and quick evaluation of the effect of traffic flow variations on vehicle emissions. However, the traditional method in developing SCFs is time consuming and costly, which impedes the development of SCFs and their applications. Based on massive instantaneous vehicle activity data, this paper proposes a novel method for deriving SCFs for light-duty vehicles on restricted access roadways in Beijing. First, a large sample of 60-s speed-specific trajectories is divided from the vehicle activity data, and grouped into speed-specific trajectory pools. Then, a database and two models of speed-specific and vehicle-specific power (VSP) distributions are established for different speed ranges. Further, by combining emission rates and VSP distributions, the SCFs for nitrogen oxides (NOx), hydrocarbons (HC), and carbon monoxide (CO) pollutants are derived for different emission standards. The derived SCFs from different sources of VSP distributions are compared with each other and validated by using another independent data source. The analysis result shows that, by using the VSP distribution database, the proposed method is applicable and effective in generating reliable SCFs in high resolution. The VSP distribution models can predict well SCFs within each speed range, while discontinuous predictions occur at their range boundary. Finally, several recommendations are made for future studies on developing comprehensive SCFs, which may help in practice to monitor dynamic traffic emissions when the real-time speed data are available. **DOI: 10.1061/(ASCE)TE.1943-5436.0000819.**

Author keywords: Vehicle emissions; Speed correction factors; Vehicle-specific power (VSP) distribution.

Introduction

Developing an accurate relationship between speed and vehicle emissions would be very helpful when monitoring traffic emission, and further evaluating the effects of congestion mitigations on emission reductions. In Chinese megacities, the traffic congestion has seriously aggravated the air pollution problems, and traffic management agencies are seeking strategies for reducing emissions by mitigating traffic congestions. As such, the variation of emissions with traffic speeds has become a key issue for evaluating the effect of congestion mitigations on emission reductions. On one hand, as an important parameter for online congestion monitoring, the average speed is widely available through the data sources of loop, remote traffic microwave sensor (RTMS), GPS, or video-based detectors in the field. On the other hand, many cities have their base emission factors based on the standard driving cycles (such as NEDC and LA92 cycles) for the purpose of estimating total emissions and developing emission inventories. Also, existing studies have demonstrated that different pollutants showed different variation patterns with the speed, which means that the effect of traffic strategies may vary for different pollutants.

The average speed has long been an important parameter in emission models. Considerable efforts have been made in developing speed correction factors (SCFs) (Brzezinski and Enns 2001), which represent the adjustments on the baseline emission factors for capturing the effects on vehicle emissions by traffic conditions associated with different average speeds. However, the traditional method in developing SCFs is costly and inefficient, and also insufficient in speed resolutions, because it relies on a series of time-consuming procedures, including collecting representative driving activity data, constructing speed correction cycles, and then testing corresponding emissions. In the newly developed emission model of MOVES (U.S. EPA 2014), besides using the predefined 47 facility-specific and speed-specific driving cycles, the model is also able to apply user-supplied trajectories to represent specific traffic conditions. However, because it is difficult to collect real-time vehicle trajectories and impractical to complete intensive computations (Frey and Liu 2013), MOVES is still difficult to meet the need of monitoring online traffic emissions by using the commonly used field traffic data.

In this context, the objective of this study is to propose an efficient approach for developing accurate and high-resolution SCFs, which can be coupled with the real-time traffic data and can be used for the online evaluation of traffic emissions.

Overview of Existing Studies

The relationships between the speed and emissions and corresponding SCFs have long been studied in traditional macroscopic

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Note. This manuscript was submitted on August 21, 2014; approved on September 30, 2015; published online on January 6, 2016. Discussion period open until June 6, 2016; separate discussions must be submitted for individual papers. This paper is part of the ***Journal of Transportation Engineering***, © ASCE, ISSN 0733-947X.

emission models, such as EMFAC (California Air Resource Board 2013) and MOBILE (U.S. EPA 2003). In developing SCFs, they first established representative driving cycles for different average speeds (or levels of service, LOS), then conducted emission tests on dynamometers according to these cycles, and further compared emission factors from each test cycle. Historically, EMFAC had several versions of SCFs, 7EP-SCF1, 7EP-SCF2, etc. (Eisinger et al. 2002), which resulted in different predictions of optimum vehicle speeds for HC, CO, and NOx emissions. Being different from EMFAC and MOBILE5, in which speed correction cycles were defined as trip-based cycles, in MOBILE6 EPA adopted facility-specific driving cycles to develop SCFs for various roadway types and congestion levels (Brzezinski and Enns 2001). In MOBILE6's SCFs for light-duty vehicles, six driving cycles were developed for freeways with an average speed ranging from 21.1 to 101.7 km/h (13.1 to 63.2 mi/h), and three driving cycles for arterial/collectors with speeds from 18.7 to 39.9 km/h (11.6 to 24.8 mi/h). The length of each cycle was around 10 min. Based on the similar method, several megacities have developed their facility-specific and speed-specific driving cycles and emission factors (Watson et al. 1982; Kamble et al. 2009; Yu et al. 2008; Hung et al. 2007). However, SCFs based on predefined driving cycles have been questionable on the following aspects: (1) whether the fixed driving cycles can adequately capture traffic characteristics on emissions (Yu et al. 2010); (2) developing driving cycles and then conducting emission testing for various road, vehicle, and speed classifications are time consuming and costly; and (3) whether the resolution of the average speed bin (or LOS) is sufficient for developing continuous speed correction curves for emissions.

Motivated by addressing disadvantages of traditional macroscopic models in depicting dynamic traffic conditions, studies on emission models have evolved from using the average speed (associated with the driving cycle) to using the road load-based parameters, such as vehicle specific power (VSP) (Jiménez-Palacios 1999). Most of the newly developed emission models, such as MOVES (U.S. EPA 2014) and IVE (Davis et al. 2005), have used VSP as the primary parameter. In VSP-based emission models, both emission rate and vehicle activities are derived by using a VSP *binning* approach (Frey et al. 2002), and running emissions in a traffic network are estimated basically by multiplying the emission rate by the time spent in each VSP bin (the so-called VSP distribution or operating mode distribution; U.S. EPA 2014), as shown in Eq. (1)

$$\text{Emission} = \text{Running Time} \times \sum (ER_i \times \text{VSP Distribution}_i) \quad (1)$$

where ER_i and $\text{VSP Distribution}_i$ are the emission rate (in units of gram per hour or second) and the percentage of the time spent (in the unit of %) in VSP bin i. As such, the new emission modeling approach has divided the research of traffic emissions into two broad branches. One is to develop emission rates for different pollutants, vehicle classes, fuel types, vehicle age, etc., by using various sources of emission test data like dynamometer, portable emission measurement systems (PEMS), remote emission sensing device (RSD), or inspection/maintenance (I/M) data (Koupal 2009). The other branch is for modeling various traffic conditions by using VSP distributions (Song et al. 2012) instead of driving cycles.

The VSP-based emission modeling approach also implies a new method for developing SCFs. If one has accurate facility-specific VSP distributions for different average speeds, SCFs could be calculated mathematically by coupling VSP distributions with emission rates, so the laboratory emissions tests according to speed correction cycles could be avoided. Frey and Liu (2013) developed SCFs for MOVES; however, it was based on fixed driving cycles instead of high-resolution speed-specific VSP distributions. Recent studies have reported encouraging progresses in modeling facility-specific and speed-specific VSP distributions. By examining speed profiles on different links for the speed bin of 30–40 km/h, Frey et al. (2006) showed that VSP distributions of different runs were not statistically different within the range of the mean speed. After comparing VSP distributions on expressways and non-expressways during peak and nonpeak hours, Song and Yu (2009) reported distinguished characteristics of VSP distributions for different road types. Based on massive second-by-second field vehicle trajectories, Song et al. (2012) found several stable regularities of speed-specific VSP distributions: (1) the VSP distribution approaches to the normal distribution when the average speed is higher than 20 km/h; (2) the mean of the VSP distribution increases monotonously with the travel speed; and (3) the mean of VSP distributions is equal to VSP values of cruising at the corresponding travel speed. These regularities are physically explainable (Song and Yu 2011): for a speed trajectory with the average speed of v, it necessarily consists of several speed subcurves with speeds higher and lower than v. Assuming that w is the vehicle power per ton (i.e., VSP) to keep the vehicle cruising at speed v, then the instantaneous VSP during this speed trajectory necessarily varies around the value of w. That is why the VSP distribution behaves in certain ways similar to the normal distribution.

The aforementioned findings are meaningful because they provide a theoretical possibility for modeling SCFs by using VSP distributions and emission rates, which may have the following potential advantages in contrast to the traditional SCFs development method: (1) it is unnecessary to develop (speed correction) driving cycles; (2) emission tests are avoided; and (3) SCFs will be in a high resolution (or continuous) if only the VSP distribution models are in a high resolution (or continuous) on the average speed.

Methodology

General methodology in this research includes four parts. First, the emission rate and the real-world vehicle activity data are collected from typical light-duty vehicles on expressways in Beijing (the type Urban Restricted Access Roadways in MOVES). Second, facility-specific and speed-specific VSP distributions database and distribution models are developed based on the existing research results. Third, SCFs are calculated by using the VSP distribution database and distribution models respectively. Finally, the accuracy of proposed SCFs is compared and their applicability is discussed. It should be stated that, as seen in Eq. (1), this study focuses on the approach of developing SCFs based on facility-specific and speed-specific VSP distributions, while the effects of vehicle age and seasonal meteorology on emission rate are not included.

Data Source and Preparation

Data Preparation of Speed-Specific Trajectories

In order to analyze characteristics of speed-specific driving activities for developing SCFs, massive vehicle activity data were collected in Beijing by using GPS devices, Garmin GPS18 and Columbus v900 GPS data loggers, mounted on 22 typical taxis of light-duty vehicles (LDVs), including the Volkswagen Jetta and Hyundai Elantra (Yu and Song 2012). The data were collected when the taxis were running and serving as usual, and no fixed routes were predesigned. Over 5.2 million records of second-by-second data were collected from 4,038 trips from 2005 to

2012. The average length of each trip was 9.4 km. Because this study focuses on the specific road type of expressways, 726,000 records of data on expressways were selected by mapping them on a GIS tool, in which the time ranged from 5:00 a.m. to 10:00 p.m., and instantaneous speeds ranged from 0 to 133.5 km/h. It should be noted that the data collected on the gradient ramps or bridges were labeled on the GIS tool, and they were not included in this study in order to avoid the impact of the road grade on the vehicle speed, acceleration, and VSP. The selected data were divided further into two groups: Group I of 355,000 records of data collected during 2011–2012 were used for the development of VSP distribution model and SCFs, and Group II of 371,000 records collected during 2005–2010 were used for validation.

All the selected data were then divided into 11,406 pieces of trajectories, each of which consist of 60 s of continuous speed data. The average speed (in units of km/h) was calculated for each trajectory by using Eq. (2). Then, each trajectory was classified into a speed-specific trajectory pool according to its average speed. The trajectory pool was defined by the average speed bin with an equal interval of 2 km/h, as shown in Eq. (3). The definitions were consistent with previous studies (Song et al. 2012)

$$\text{Average Speed} = \frac{\text{Distance Traveled}}{\text{Time Spend}} = 3.6 \times \frac{\sum_{i=1}^{60} v_i}{60} \tag{2}$$

$$\forall{:}\text{Average Speed} \in [n-1, n+1), \text{Speed bin\#} = n \quad (n \text{ is an integer}, n > 20) \tag{3}$$

where v = vehicle instantaneous speed in the unit of m/s and *Speed bin#* = ID of the speed-specific trajectory pool. It should be noted that two reasons are considered in dividing the raw second-by-second speed profile into smaller trajectories with a 60-s time interval: (1) a long speed profile, like a 10-min driving cycle, may contain too much traffic pattern information to produce stable and repeatable speed-specific VSP distributions, which is also why the fixed driving cycle is difficult to represent the real-world traffic; and (2) in traffic monitoring systems, the field traffic data [from remote traffic microwave sensor (RTMS), loop, or floating car data (FCD)] are commonly updated at 1-min, 2-min, or 5-min intervals, so VSP distributions based on the 60-s interval would be more compatible for estimating dynamic emissions by using online traffic data. Consequently, a total of 57 speed-specific trajectories pools were constructed for the average speed ranging from 3 to 115 km/h.

Data Preparation of Emission Rate

Emission rates (in units of g/h, as shown in Fig. 1) of NOx, HC, and CO pollutants were derived from an emission database (Yu and Song 2012) in Beijing Jiaotong University. Since 2003, 52 light-duty gasoline vehicles were tested by using the portable emission measurement systems (PEMS). Mass emissions of NOx, HC, and CO from the tailpipe exhaust and the corresponding vehicle speed and acceleration were collected on a second-by-second basis. The vehicles were classified into five groups according to the regulatory emission standards, named China 0 (pre-China I), I, II, III, and IV, which are nearly identical to Europe's emission standards in terms of the limit value, test cycle, and other parameters. A strict quality control process was conducted on the emission data, including (1) synchronization of system time between PEMS gas analyzers, GPS receiver, and engine data; (2) identification of missing and jumping of engine data from sensor array including RPM, intake air pressure, and temperature; (3) elimination of leakage and flooding error of emission sampling system; (4) correction of zero-level drift of gas analyzers; and (5) identification of missing and jumping of GPS signals. In addition, a finer time alignment between GPS and PEMS gas analyzer was conducted separately for NOx, HC, and CO by calculating the Pearson correlation coefficient between emissions and the corresponding positive VSP values. The alignment with the maximum correlation coefficient was considered as the best time alignment. A total of 442,539 records of second-by-second mass emission data of 8, 12, 9, 11, and 8 LDVs were selected from the database for China 0, I, II, III, and IV emission standards. For each record of emission data, the VSP value was calculated according to its instantaneous speed and acceleration by using a typical VSP equation for LDV (Jiménez-Palacios 1999), as Eq. (4),

$$\text{VSP} = v \times [1.1 \times a + 9.81 \times \text{grade} + 0.132] + 0.000302 \times v^3 \tag{4}$$

where v = instantaneous speed (m/s); a = acceleration (m/s^2); and *grade (%)* = vehicle vertical rise divided by the slope length, which is assumed to be zero because the emission data collected on the gradient ramps or bridges were excluded in this study. Then, emission rates for different emission standards were calculated by grouping the raw second-by-second emission data into each VSP bin, as shown in Fig. 1. The VSP binning method in this study will be provided in the next section.

Development of VSP Distribution Database and Models

VSP Binning Method

VSP bins have to be defined in advance in order to calculate emission rates and VSP distributions, and thus running emissions, as shown in Eq. (1). In previous studies of modeling traffic characteristics based on VSP distributions (Song et al. 2012; Song and Yu 2011), VSP bins were defined by using an equal VSP interval of 1 kW/t so as to reveal quantitative correlations between the VSP distribution and the average speed. In this paper, different binning methods were applied for the parts of VSP > 0, VSP $= 0$, and VSP < 0.

For VSP > 0, a similar binning method as those in reference (Song et al. 2012) was applied, as shown in Eq. (5)

$$\forall{:}\text{VSP} \in [n, n+1), \text{VSP bin} = n \quad (n \text{ is a positive integer from 0 to 25}) \tag{5}$$

The VSP value of 0 was defined as an independent VSP bin because it was known that vehicles generally emit the lowest emission rate when VSP $= 0$ (i.e., in idling condition) (U.S. EPA 2002, 2011). For VSP < 0, the whole negative VSP side was combined and defined as one bin because emission rates in the negative VSP side were found nearly identical (U.S. EPA 2011).

VSP Distribution Database

Based on the preceding VSP bin definitions, for both Group I and Group II speed-specific trajectory pools, the VSP distributions were calculated for each of 35 speed-specific trajectory spools with the average speed ranging from 3 to 71 km/h. Other trajectory pools with higher average speed were not included in calculating VSP distributions because insufficient samples (less than 20 trajectories) may lead to errors in representing corresponding traffic conditions. Calculation results were stored into Group I and Group II VSP distribution databases separately. The table structure of the VSP distribution database is illustrated in Table 1.

J. Transp. Eng., 2016, 142(3): 04016001

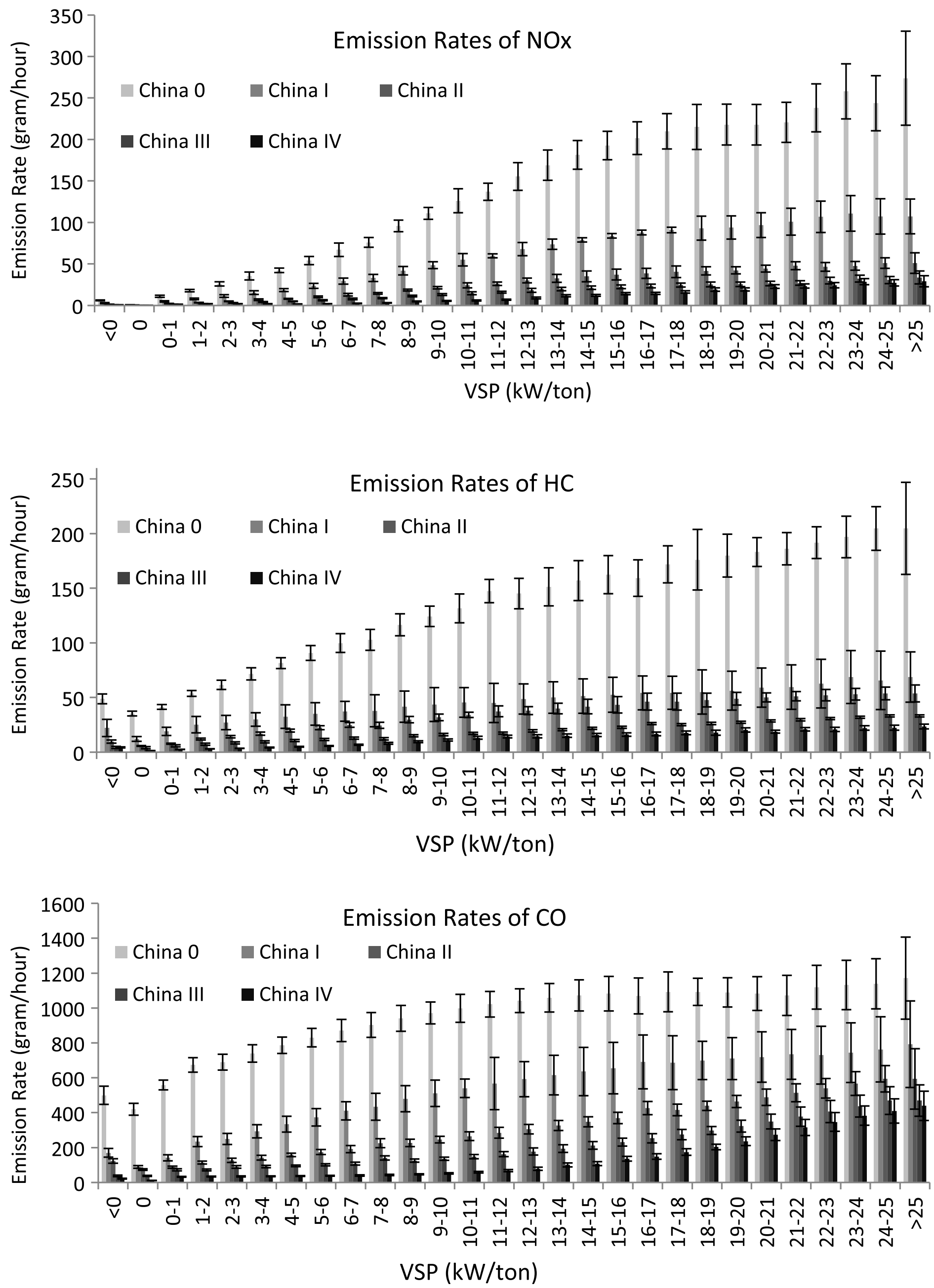

Fig. 1. Emission rates of different emission standards

Theoretically, a VSP distribution database (as shown in Table 1) is sufficient for deriving speed-specific emission factors and further SCFs by using emission rates in Fig. 1 and Eqs. (1), (14), and (15). However, for those cities that do not have VSP distribution database, the existing VSP distribution models (Song et al. 2012; Song and Yu 2011) provide a possibility to develop local SCFs by integrating VSP distribution models with local emission rates. Therefore, this study further investigated the feasibility of modeling SCFs based on existing VSP distribution models by using the Group I VSP distribution database.

VSP Distribution Models

Two VSP distribution models have been proposed separately for the average speed higher and lower than 20 km/h, because they exhibit distinguished regularities. For the average speed higher than 20 km/h, the VSP distribution follows a normal distribution, in which the mean of the VSP distribution was the VSP value when cruising at the average speed and the standard deviation was expressed as a power function of the average speed. The probability density function for VSP was given by Eq. (6) (Song et al. 2012)

$$f(\mathrm{VSP}) = \frac{1}{\sigma\sqrt{2\pi}} e^{-(\mathrm{VSP}-\mu)^2/2\sigma^2} \quad (\text{for } s > 20 \text{ km/h}) \qquad (6)$$

where μ and σ could be calculated by using the functions of the average speed s (km/h), as shown in Eqs. (7) and (8), respectively. Eq. (7) was derived from Eq. (4) by setting a and *grade* to zero

$$\mu = 0.132 \times \frac{s}{3.6} + 0.000302 \times \left(\frac{s}{3.6}\right)^3 \quad (\text{for } s > 20 \text{ km/h}) \quad (7)$$

Table 1. Illustration of Group I VSP Distribution Database

	VSP bin								
Average speed (km/h)	VSP < 0 (%)	VSP = 0 (%)	(0, 1] (%)	(1,2] (%)	(2,3] (%)	(3,4] (%)	...	(24, 25] (%)	>25 (%)
3	14.5	60.7	14.5	3.1	2.1	1.8	...	0.0	0.0
5	20.3	48.6	18.1	5.3	2.7	1.3	...	0.0	0.0
7	24.1	34.1	24.0	8.1	3.4	2.0	...	0.0	0.0
9	26.5	24.9	24.5	9.7	5.2	3.2	...	0.0	0.0
11	27.1	24.1	21.3	10.9	5.5	3.2	...	0.0	0.1
...	...	...	...	...	...	...	...	...	...
69	10.2	0.0	4.6	5.8	7.0	8.0	...	0.0	0.0
71	9.4	0.0	4.3	5.5	6.6	7.7	...	0.0	0.1

$$\sigma = 0.885 \times s^{0.4073} \quad (\text{for } s > 20 \text{ km/h}) \tag{8}$$

Because the VSP binning method in this study has been modified according to the emission rate in idling conditions, as shown in Table 1, the fraction of VSP $= 0$ cannot be predicted by using this probability density function. Therefore, the fraction of VSP $= 0$ was modeled separately based on a regression analysis on the Group I VSP distribution database. As shown in Fig. 2(a) and Eq. (9), the fraction of VSP $= 0$ can be expressed as a power function of the average speed, in which the regression R^2 is 0.96

$$\text{VSP Fraction}_{\text{VSP}=0} = 0.8998 \times e^{-0.127 \times s} \tag{9}$$

For the average speed lower than 20 km/h, Song and Yu (2011) modeled VSP distributions for negative VSP bins, zero bin ($-0.5 \le \text{VSP} < 0.5$), and positive bins separately. A similar modeling approach was adopted with slight modifications according to the new VSP bin definition. The fraction of $0 < \text{VSP} < 1$ was modeled as shown in Fig. 2(b). A cubic function was found to be able to describe the relationship between the VSP fraction and the average speed with a regression R^2 of 0.799, as provided in Eq. (10)

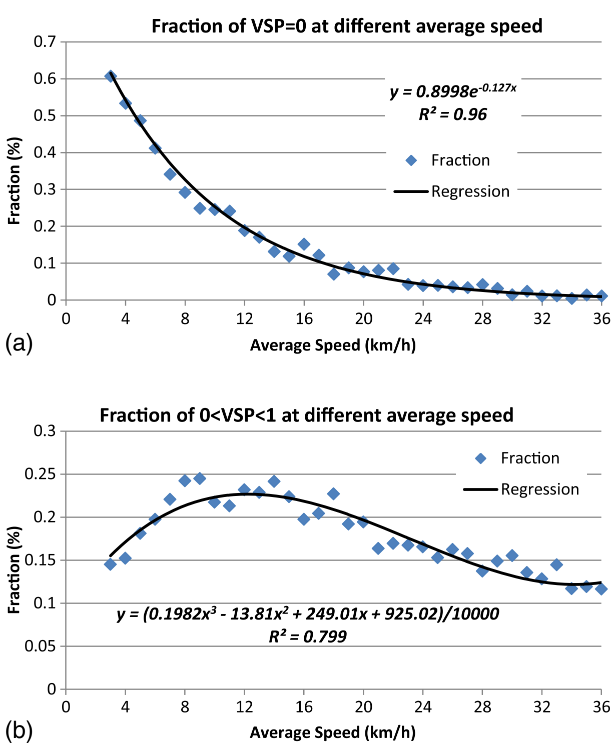

Fig. 2. Fraction of VSP $= 0$ and $0 \le \text{VSP} < 1$ at different average speed: (a) fraction of VSP $= 0$; (b) fraction of $0 < \text{VSP} < 1$

$$\text{VSP Fraction}_{0<\text{VSP}<1} = 0.1982 \times s^3 - 13.81 \times s^2 + 249.01 \times s + 925.02/10{,}000 (\text{for } s \le 20 \text{ km/h}) \tag{10}$$

For negative VSP bins, because the whole negative side was defined as one bin, the fraction of VSP < 0 was regressed based on values in Table 1. The regression result is provided in Eq. (11) with an R^2 value over 0.95

$$\text{VSP Fraction}_{\text{VSP}<0} = -6.5837 \times s^2 + 226.16 \times s + 1{,}166.2/10{,}000 \quad (\text{for } s \le 20 \text{ km/h}) \tag{11}$$

For positive VSP bins, since the absolute fractions dropped rapidly to very low values (around 10^{-3} when VSP bin > 7), a transformation was applied, in which the original fractions were logged to the base e. It was found that the quadratic functions fit well the relationship between $-\ln(\text{VSP Fraction})$ and the VSP bin number. After examining all the regression results of the average speed from 3 to 20 km/h, the $-\ln(\text{VSP Fraction})$ values were expressed as Eq. (12)

$$-\ln(\text{VSP Fraction} = A \times \text{VSP bin}^2 - B \times \text{VSP bin} + C \quad (\text{for } s \le 20 \text{ km/h}) \tag{12}$$

where VSP bin is the VSP bin number, and A, B, and C are constant coefficients, as listed in Table 2.

Table 2. Regression Coefficients and R-Squares for Different Average Speeds

	Positive VSP side			
Average speed (km/h)	A	B	C	R^2
3	−0.0153	0.505	3.21	0.96
4	−0.0226	0.608	2.59	0.98
5	−0.0160	0.524	2.78	0.98
6	−0.0122	0.526	2.49	0.97
7	−0.0166	0.594	2.19	0.97
8	−0.0178	0.639	1.95	0.94
9	−0.0149	0.571	1.92	0.97
10	−0.0152	0.610	1.75	0.97
11	−0.0187	0.649	1.53	0.96
12	−0.0198	0.639	1.54	0.99
13	−0.0184	0.669	1.35	0.98
14	−0.0140	0.618	1.41	0.97
15	−0.0174	0.632	1.31	0.98
16	−0.0062	0.481	1.58	0.99
17	−0.0091	0.531	1.47	0.96
18	−0.0101	0.587	1.20	0.99
19	−0.0074	0.509	1.38	0.99
20	−0.0056	0.459	1.51	0.97

Table 3. Baseline Emission Factors

Pollutants	Emission factors (g/km) China 0	China I	China II	China III	China IV
NOx	1.08	0.47	0.21	0.13	0.07
HC	2.01	0.79	0.46	0.25	0.14
CO	19.76	7.69	4.31	2.48	1.12

Regular variation patterns were observed for A, B, and C along with the average speed. Regression models were further developed to describe the relationship between coefficients A, B, and C and the average speed, as shown in Eq. (13). So far, by combining Eqs. (6) to (13), mathematical VSP distribution models have been established based on Group-I database, which are able to predict VSP distributions based on the average speed

$$A = 0.8459 \times s^2 - 13.724 \times s - 120.65/10{,}000, \quad R^2 = 0.68 \tag{13a}$$

$$B = -21.25 \times s^2 + 475.89 \times s + 3{,}636.45/10{,}000, \quad R^2 = 0.65 \tag{13b}$$

$$C = -6.4049 \times s^3 + 339.56 \times s^2 - 5{,}971.7 \times s + 48{,}891/10{,}000, \quad R^2 = 0.96 \tag{13c}$$

Development of SCFs

SCFs were calculated by using Eq. (14), where EF_S stands for the emission factor (g/km) at the average speed of s (km/h), which can be calculated by Eqs. (1) and (15), and EF_B is the emission factor for the baseline driving cycle

$$SCF_S = EF_S/EF_B \tag{14}$$

$$EF_S = Emission_S/Average\,Speed_S \tag{15}$$

where $Emission_S$ is total emissions per running hour.

The NEDC driving cycle was used as the baseline driving cycle for calculating EF_B, because it is the regulatory cycle in China for testing base emission factors. The 1,180-s NEDC cycle consists of four repeated ECE-15 urban cycles and an extra-urban cycle, with a total distance of 11.02 km and an average speed of 33.6 km/h. After calculating NEDC's VSP distribution, and combining it with NOx, HC, and CO emission rates in Fig. 1, baseline emission factors for each pollutant at each emission standard were derived by using Eqs. (1) and (15), as listed in Table 3.

Four sets of speed-specific emission factors were then derived based on four sources of VSP distributions: (1) Group I VSP distribution database, which is termed VDB-Group-I; (2) Group II VSP distribution database, which is used for validation, and termed VDB-Group-II; (3) VSP distribution model for the average speed lower than 20 km/h, termed VDM-Low; and (4) VSP distribution

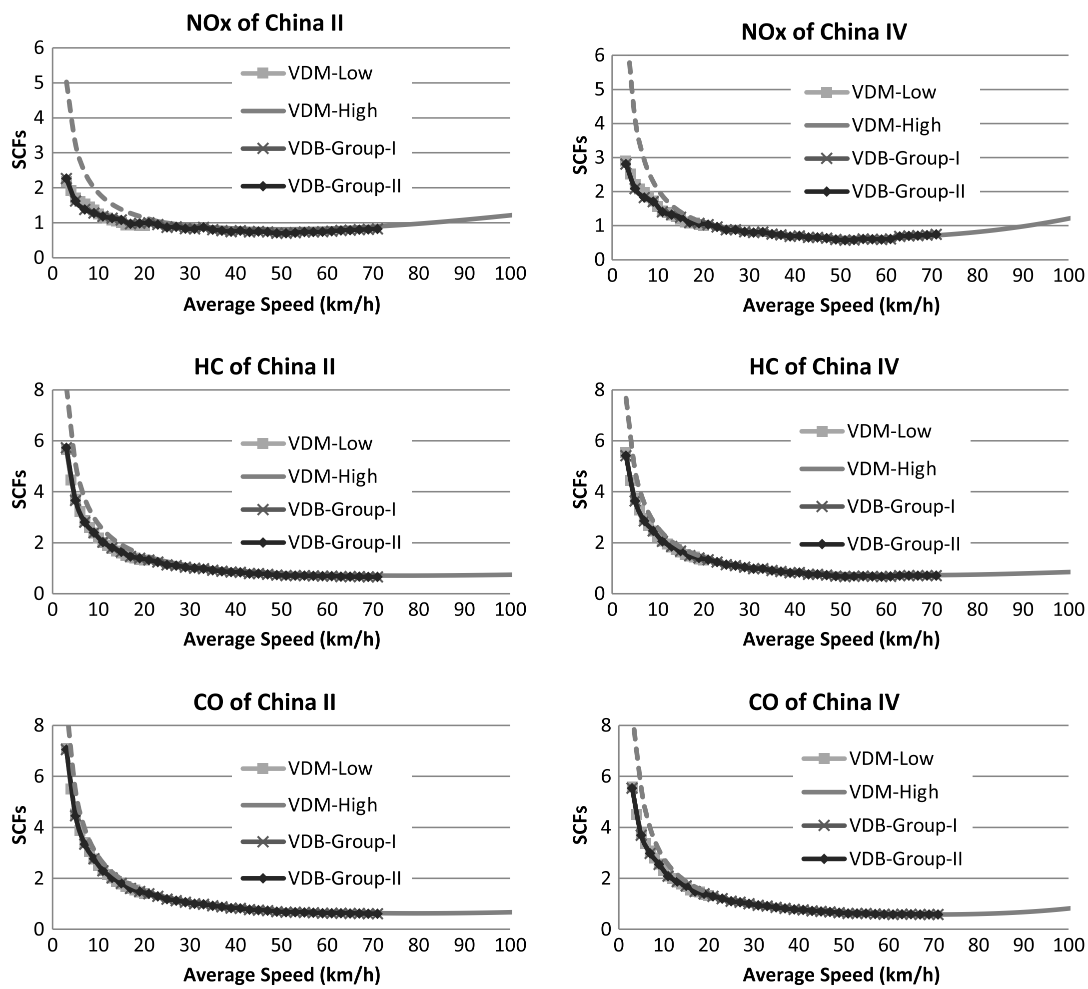

Fig. 3. SCFs based on three sources of VSP distribution

model for the speed higher than 20 km/h, termed VDM-High. Then, by using Eq. (14) and the values in Table 3, four sets of SCFs were calculated, as shown in Fig. 3.

Discussion

It was observed from Fig. 3 that the SCFs generated from the Group-I VSP distribution database are nearly identical to the ones from validation group (Group-II VSP distribution database), and their SCF curves overlap each other. After examining all the SCFs derived by the two VSP distribution databases, it was found the relative differences of two sets of SCFs were less than 2% for all pollutants and emission standards, which indicated that the SCFs developed based on VSP distributions in this study are repeatable and reliable. In terms of the SCFs' variation pattern, the pollutants HC and CO were of similar value with a wide variation range, approximately from 0.5 to 7. The value dropped rapidly with the increase of the speed in the low-speed range and increased slowly in the high-speed range. However, the SCFs curve of NOx was much flatter than those of HC and CO. Its variation range was approximately from 0.7 to 3, which indicated that NOx is relatively less sensitive to speed than the other two pollutants. For HC and CO, their SCFs predicted the minimum emission point at approximately 80 km/h. However, the optimal speed for NOx was around 52 km/h. Similarities can be found between these results and those of freeway SCFs in MOBILE6 (Brzezinski and Enns 2001).

In terms of the feasibility of modeling SCFs based on the existing VSP distribution models, when the average speed was higher than 20 km/h, the normal distribution-based VDM-High model predicted smooth and consistent SCFs curves compared to the VDB-Group-II. However, in the speed range lower than 20 km/h, there were considerable discrepancies between SCFs generated by the VDM-High and VDB-Group-II. In terms of the VDM-Low model, it generated well-matched SCFs curves in the speed range lower than 20 km/h. Though either VDM-High or VDM-Low was able to predict well SCFs within its modeling range of speed, they were not continuous at the point of 20 km/h, where the SCFs derived by VDM-High was higher than those by VDM-Low for all pollutants.

It may need to be noted that this paper used NEDC as the base cycle, with the average speed of 33.6 km/h; however, SCFs at 33.6 were approximately 0.8 for NOx and 0.95 for HC and CO, instead of 1. Reasons can be attributed to two aspects: 1)) NEDC is a trip-based cycle, which combines both urban (average speed 18.8 km/h) and extra-urban (average speed 62.6 km/h) cycles, while the trajectory pool in this study consisted of facility-specific and speed-specific, 60-s trajectories; and (2) the road type in this study was expressways (urban restricted access roadways), so there existed less driving modes of idling, deceleration, and acceleration than unrestricted access roadways. Therefore, the 60-s speed-specific trajectories on expressways with the average speed 33.6 km/h tended to generate lower emissions than the NEDC cycle.

Because the speed limit of most expressways in Beijing is 80 km/h, this study did not have sufficient trajectory samples for deriving VSP distributions and SCFs for the average speed higher than 71 km/h. By assuming that the speed-specific VSP distribution still follows the normal distribution in the average speed ranging from 71 to 120 km/h, the VDM-High model was applied to extrapolate SCFs based on the real VSP distribution database, as shown in Fig. 4. However, the extrapolation needs to be further validated.

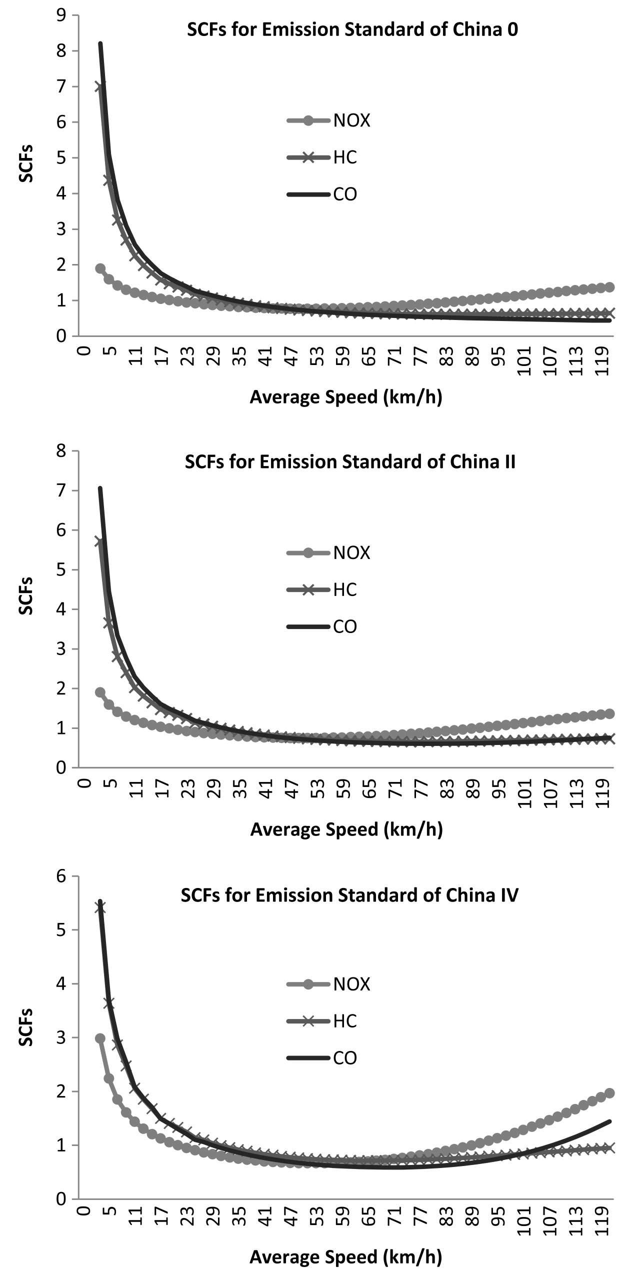

Fig. 4. SCFs of NOx, HC, and CO for restricted access roadways

Summary and Recommendation

Based on massive LDV field activity data, a large sample of speed-specific 60-s trajectories was created for establishing speed-specific VSP distributions. A practical method for developing SCFs was then proposed based on VSP distributions and emission rates, which was applicable and was able to generate repeatable SCFs for different pollutants. The proposed method has the following advantages:

1. It does not need the traditional process in developing driving cycles and the emission testing for different speeds or LOS. On one hand, this process is considerably costly and time consuming. On the other hand, the method of developing a driving cycle has long been questionable about how to ensure the cycle's representativeness on facility-specific and speed-specific driving characteristics;
2. It is able to generate SCFs in a high-resolution manner. In contrast to the traditional SCFs on large speed intervals or LOS, the

new SCFs can be more continuous with the speed as long as sufficient speed-specific trajectories are available. It will be helpful for the online emission modeling and developing the high-resoluted temporal and spatial emission distributions on a dynamic traffic network; and
3. More flexibility is provided for developing various kinds of SCFs for different road classes, vehicle types, and management measures. In the proposed method, developing VSP distributions and emission rates involve two independent procedures. Given that the MOVES model has provided a huge and comprehensive emission rate database, developing the speed-specific VSP distribution is the only need for deriving SCFs. The only input for developing VSP distributions is to collect vehicle trajectories or using a reliable VSP distribution model; therefore, it would be more flexible for traffic engineers to develop SCFs to meet their practical needs.

This paper provides a method for deriving SCFs on urban expressways. Further studies are recommended to improve the proposed approach. First, trajectories with average speeds over 71 km/h need to be collected. Second, the effect of road grade on SCFs needs further investigations by measuring accurate grade or altitude data. Third, for the type of unrestricted roadways, 60-s speed-specific trajectories may not be sufficient to cover all driving characteristics of both on roads and at intersections. A longer and proper trajectory length needs to be further analyzed.

Acknowledgments

This research is supported by the National Basic Research Program of China #2012CB725403, the Natural Science Foundation of China (NSFC) #71273024 and 51208033, the Fundamental Research Funds for the Central Universities #2014JBM060.

Notation

The following symbols are used in this paper:

A = vehicle acceleration in the unit of m/s^2;
Emission_s = total emission per running hour (g);
EF = emission factor (g/km);
ER = emission rate (g/h);
Grade (%) = vehicle vertical rise divided by the slope length in the unit of %;
i = number of VSP bin;
n = positive integer from 0 to 25;
s = average travel speed (km/h);
v = vehicle speed (m/s);
VSP = vehicle specific power (kW/t);
$\text{VSP Distribution}_i$ = percentage of the time spent in VSP Bin i (%);
μ = mean of normal distribution; and
σ = standard deviation of normal distribution.

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