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Analysis of the Characteristics of Real-World Emission Factors and VSP Distributions—A Case Study in Beijing

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Abstract: Vehicle emissions intensity at a given travel speed is well known among the public since travel speed is the key parameter in both the traffic model and the emission model. Yet, several problems still remain in traditional approaches of measuring the emission intensity. To establish accurate and high-resolution emission factors, an established method of emission factors is proposed based on the real-time monitoring operation conditions data, which can reflect the effect of dynamic traffic changes on emissions. The speed-specific vehicle-specific power (VSP) distributions of different months, as well as those in different vehicles in Beijing were developed and compared. Statistical analyses such as Coefficient of Variation (CV) and Root Mean Square Error (RMSE) were used to quantify the differences in the VSP distribution. The results showed the significant correlation between the distribution of VSP, velocity, and operating patterns at time intervals within the annual range. Driving conditions in 2021 are more eco-friendly because of the improvement of digital development and driving habits. Furthermore, research on CO, HC, and NOx emission factor situations in different cycles revealed that the emission factors of NOx and HC are always underestimated in typical operating modes, while sometimes the emissions of CO are overvalued.

Keywords: VSP distribution; operating mode distribution; dynamic emission factor estimation

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Citation: He, W.; Duan, L.; Zhang, Z.; Zhao, X.; Cheng, Y. Analysis of the Characteristics of Real-World Emission Factors and VSP Distributions—A Case Study in Beijing. *Sustainability* **2022**, *14*, 11512. https://doi.org/10.3390/su141811512

Academic Editors: Yusheng Ci, Lina Wu and Ming Wei

Received: 25 June 2022
Accepted: 6 September 2022
Published: 14 September 2022

1. Introduction

Today, with the development of big data in the transportation industry, the quantitative evaluation of motor vehicle emissions tends to from macro to micro research. In addition, the evaluation of the effect of energy-saving and emission reduction restricting the traffic congestion remission policy becomes quantifiable. Thence, the travel speed is invariably the key parameter in both the traffic model and the emission model, and therefore vehicle emissions intensity at a given travel speed is well known among the public. Yet, there are still several problems within the traditional way of measuring the emission intensity. For instance, the traditional approach owns the significant limitation which is the speed recognition and traffic data usage of traditional methods remains low. Moreover, even though it can help the decision-making process of macroscopic policy, it cannot give microcosmic evaluation, which makes it impossible to achieve effective traffic management. For vehicle emissions, the actual emission factors include vehicle manufacturing properties, vehicle maintenance status (e.g., I/M system, a system to minimize the pollution caused by in-use motor vehicles through regular and irregular emission testing and mandatory maintenance of vehicles that do not meet the emission standards, so that in-use motor vehicles can reach or approach their optimal emission levels through continuous treatment), and traffic conditions. When establishing emission factors, traditional emission models such as EMFAC, MOBILE [1], and HBEFA model [2] consider the first two factors in more detail, while the typical conditions are chosen to replace the actual conditions when the traffic conditions are considered. Taking MOBILE and HBEFA models as examples, these models generally consider the emission characteristics under typical working conditions. For instance, HBEFA investigates the closest one typical working condition among numerous samples as the working condition for emission characteristics description. In other words, when they then describe the emission characteristics, they mainly consider typical conditions rather than actual working conditions.

To better illustrate the research perspective of this study, the concept of the driving cycle is introduced. Driving cycle, also known as the vehicle test cycle, is a description of the speed-time curve of the vehicle, reflecting the kinematic characteristics of the vehicle road driving; is an significant, common basic technology in the automotive industry; and is the basis of the vehicle energy consumption/emission test methods and limit value standards, but also the main benchmark of the vehicle performance indicators calibration optimization. To deeply understand the above-mentioned conditions, this study focuses on light-duty vehicles only, such as taxis.

At the same time, in the traditional emission models, the driving cycles in different average speed intervals or service levels (Levels of Service, LOS) are established, and then the emission factors of each driving cycle are obtained by using the bench test or micro model, such as PHEM [2]. Unlike the MOBILE, the EMFAC model has different emission factor calculation methods, such as 7EP-Selective Catalytic Reduction (SCF) (1 and 7EP-SCF2 [3], leading to different emission results). Compared to the EMFAC and MOBILE5 models, the MOBILE6 EPA and MOBILE6 models not only consider the speed when establishing the driving cycle but also take into account the vehicle's driving conditions and the environment, including road type and congestion level [4]. Based on these findings, some megacities have established a driving cycle based on specific speed and driving conditions and have obtained emission factors through testing [5]. In addition, current studies perform environmental analysis from different perspectives for emission factors. Sun et al. estimated GHG emission factors based on urban transportation big data to explore whether shared transportation schemes can reduce GHG emissions [6]. However, the emission factor establishment method based on a fixed driving cycle is questioned in the following aspects.

Firstly, it may be questionable whether a fixed driving cycle accurately reflects the actual driving characteristics of the vehicle [7]. An optimization-based method is needed to develop a representative driving cycle for real-world fuel consumption estimation. Secondly, the process of establishing driving cycles and testing emission at different vehicle types and speed intervals highly increase time cost. Finally, it is uncertain whether the resolution of the average speed or the level of service of the emission factor obtained by the method can meet the requirements for establishing a continuous speed emission correction curve.

In view of the shortcomings of the traditional establishment method of emission factors in the aspect of reflecting the actual driving characteristics of the vehicle, many scholars investigate the relationship between instantaneous traffic parameters and emissions, such as vehicle specific power (VSP) distribution [8]. Traditional models such as HBEFA use parameters including RPA (stopping ratio) as one of the factors to realize the typical operating conditions, while some models such as MOBILE directly apply the characteristic results under typical operating conditions as the base emission factor. The application of VSP parameters is used from models such as IVE and MOVES. A number of new emission models, such as MOVES and IVE, all use VSP distributions as the key parameters. VSP is the output power of the motor vehicle corresponding to each unit of mass towed by the engine, it indicates the power of the engine to overcome rolling resistance and air resistance to manipulate, as well as the power needed to increase the kinetic and potential energy of the motor vehicle issued in kw/ton or m^2/s^3. VSP is a comprehensive indicator of the dynamics of the vehicle, the physical quantity has a vectorial nature; when the vehicle brakes slow down, VSP will appear to be negative when the vehicle brakes decelerate. It has been used in a number of studies as a proxy for the amount of emissions. A related study currently defines the VSP distribution (or Op Mode operating mode in MOVES) as the percentage of time spent in each VSP bin [9]. In addition, 23 operating modes of vehicle start-stop and exhaust processes are identified in MOVES based on VSP, vehicle speed, and acceleration [10].

As metioned, many researchers have investigated VSP distributions. For instance, to evaluate the effectiveness of the fit of the VSP distribution, Yu et al. [11] used root mean square error (RMSE) to assess the difference between two VSP distributions. RMSE is a standard way to measure the error of a model in predicting quantitative data. Zhang et al. [12] discussed in detail how the SCF responds to the characteristics of the VSP distribution and emission rate changes and showed that distortion of the VSP distribution and emission rate had a significant effect. Rosero et al., by developing a test scenario in a driving simulator, established the effects of passenger load, road class, and congestion levels on the actual fuel consumption and emissions of compressed natural gas and diesel city buses [13]. Acuto et al. assessed the environmental performance of urban roundabouts using the VSP method and AIMSUN [14]. Zhou et al. identified the spatial and temporal characteristics and drivers of road traffic CO emissions [15], first using a classical OLS model, and later analyzing the influencing factors using geographically weighted regression. The relationships between the independent and dependent variables are considered to be smooth, meaning that these relationships do not vary spatially. There are also new approaches to emission model construction based on machine learning methods, Mądziel et al. applied the VERSIT+ emission model to the small-scale analysis of vehicular traffic emissions at multi-lane roundabout intersections [16] using PEMS data as training data for the model and as validation data for the model [17]. Jaworski et al. explored the impact of different bus fleet variants on GHG emissions by differentiating bus pairs by type [18]. The models generated by this method can be used to analyze emissions from simulation tests or can be used as input parameters for speed, acceleration, and road slope.

It can be seen that the VSP-based emission modeling method provides a theoretical basis for the new emission factor approach. The fitting and modeling methods applied in the above models are summarized in the following section. The fields within climate and environment were mainly introduced by the RMSE studies; however, the RMSE as a measure of mean error has significant errors because the RMSE is a characteristic function of the error rather than the mean error. Taking RMSE and MAE as examples, they have the same magnitude, but when the results are derived, we find that RMSE is larger than MAE. This is because RMSE is the accumulation of the square of the error before opening the square; it actually amplifies the gap between the larger errors whereas MAE responds to the true error. Therefore, the smaller the value of RMSE in the measurement, the greater its significance, because its value reflects that the maximum error of the model is also relatively small (in simple terms, that is, the value of RMSE is generally larger than MAE, so RMSE is small then MAE must be small, and MAE is small, RMSE is not necessarily small, so directly looking at RMSE is better). While the classical OLS model assumes that the relationships between the independent and dependent variables are smooth, meaning that these relationships do not vary spatially, the later optimization uses a geographically weighted regression (GWR) that assumes a non-smooth relationship between the independent and dependent variables, but it implicitly assumes that each independent variable has the same spatial scale, which again has an impact on the fitted results. For related simulation studies, particularly in the area of transport gas emissions, this can have an impact on the prediction results due to the fact that there are fewer data at a finer, more differentiated level of real-world granularity. It is, therefore, necessary to create national and regional emission models at the microscale, as this allows us to obtain detailed results on the emissions generated by vehicles passing through a particular road type. It can be seen that the VSP-based emission modeling method provides a theoretical basis for the new emission factor approach. If the VSP distribution with different mean speeds can be accurately obtained, the VSP distribution can be multiplied by the emission rate to obtain the emission factor, thus avoiding the establishment of a fixed travel cycle and a large number of bench test processes. The above analysis shows that the previous studies are deficient in terms of research accuracy, selection of mathematical and statistical methods, data volume, and most notably, in the lack of description of the vehicle driving state and the lack of precision of the obtained emission factors.

Therefore, the objective of this paper is to obtain emission factors with high emission rates, which in turn accurately describe the vehicle state. Compared with the traditional emission factor establishment method, this method has the following advantages.

First and foremost, the method can accurately describe the driving condition of the vehicle based on the high-resolution VSP distribution established upon a large number of measured condition data compared with the fixed driving cycle. Secondly, the method can take advantage of the approved VSP-based vehicle emission rate, without the need for a large number of tests or numerical simulations for each emission standard, vehicle age, and vehicle under each mileage. Last but not least, the method makes full use of the growing traffic data resources, uses trajectory data to establish VSP distribution to acquire high-resolution factors, and the factors will be given a dynamic new life to support micro-traffic behavior assessment.

2. Methodology

In order to obtain the real emission factors for the road network in Beijing directly, and to calculate the traffic operating conditions and emission factors of different vehicle individuals at different times, this study has three steps, as follows:

(i) Massive second-by-second data of vehicle activity data of taxis in Beijing (Referred to as "BJ taxi") are collected by employing the vehicle monitoring platform or GPS devices. The platform continuously collects emission factors and shares vehicle information through intelligent means, enabling analysis of typical vehicle driving conditions, and micro-emissions-based monitoring. The data of taxi CO, HC, and NOx emission rates (ER, g/s) are obtained based on portable emissions monitoring systems (PEMS). Both these types of data were necessary for modeling input parameters. In the VSP-based emission model, both the VSP distribution and emission rates are derived by using a VSP binning approach. The VSP distribution determines the traffic network, and the emission rates in various VSP bins represent the vehicle emissions under different power demands, which gather from PEMS or chassis dynamometers. The running exhaust emissions are estimated basically by multiplying the emission rates with the VSP distribution [10], as shown in Equation (1).

$$\text{Emission} = \text{RunningTime} \times \sum_{\text{VSPbin}} (\text{EmissionRate} \times \text{VSPdistribution}) \quad (1)$$

As shown in Figure 1, we obtained metadata from mobile source emission testing room and survey and collection platform work data, and performed VSP calculation after data cleaning to obtain VSP-bin distribution and VSP-bin emission rate. After obtaining the VSP-bin distribution, we analyze them for time difference distribution, vehicle difference distribution, and typical working conditions, and after obtaining the emission rate, we conduct the characterization and study of emission factors for typical working conditions.

(ii) The VSP distribution is established in accordance with the VSP interval differentiate patterns such as type of Op mode VSP interval, and different average speed by big data processing platform.

(iii) Statistical analyses, such as Coefficient of Variation (CV), (Root Mean Square Error (RMSE), etc. are applied to quantify the differences of the VSP distribution of VSP distribution on emission factor. Finally, this study establishes different levels of emission factors and evaluates the accuracy of the results.

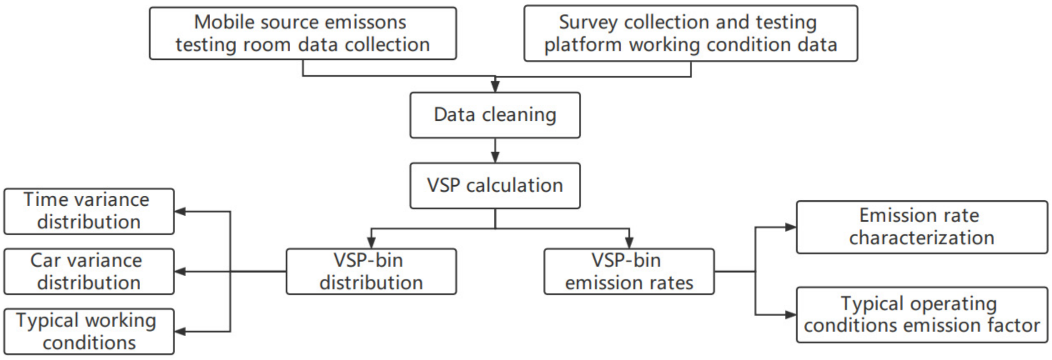

Figure 1. Technical framework.

2.1. Data Sources

The data sources in this study mainly include two parts:

(i) Second-by-second vehicle activity data of the taxi car which is the key data in this study. A total of 22.7 billion records of second-by-second real-world activity data of BJ taxi were collected with GPS devices in Beijing Statistics and Monitoring Platform of Transport Energy Saving and Emission Reduction (BSMP-BTEC) over the past 6 months and stored in the database in Beijing Transport Institute (BTI). As shown in Figure 2, it is the interface diagram of Beijing's transportation energy saving and emission reduction statistics and testing platform, which covers the full coverage of working conditions of 157 vehicle models and operating vehicle models. It can collect diversified traffic emission data. For the last eight years, we have selected three years of data at four-year intervals by using a longitudinal approach. The data are provided by more than 700 vehicles, as listed in Table 1. Other details about the data are listed as follows:

Collection period, 2013–2017–2021
Collection Time, from 0:00 a.m. to 12:00 p.m.
Longitude and Latitude
Instantaneous Speed, from 0 to 130 km/h
Details about the activity data of the BJ taxi will be described below:

Figure 2. Beijing Transportation Energy Saving and Emission Reduction Statistics Monitoring Platform.

Table 1. The data size of vehicle activity data.

Index	Year		
	2013	**2017**	**2021**
Sample size (million Records)	12.12	226.20	149.63

(ii) Second-by-second emissions data of the 2-year-old taxi gasoline vehicles. In order to ensure the comparability of emissions under real operating conditions, a 2-year-old quasi-new vehicle was selected as the input of emission rate to remove the effect of emission rate on the difference of operating conditions. In this study, the emission rate is an crucial input parameter, but not the key research content. This study has constructed the emission rate database covering 23 VSP intervals based on the test data.

2.2. VSP Binning Method

VSP is the instantaneous tractive power per unit of vehicle mass. It is calculated with the method provided by the MOVES, as shown in the following equations.

$$a_t = v_{t+1} - v_t \tag{2}$$

$$VSP_t = (A \cdot v_t + B \cdot {v_t}^2 + C \cdot {v_t}^3)/m + (a_t + g \cdot sin\theta) \cdot v_t \tag{3}$$

where

v_t, v_{t+1} are the vehicle speeds at time t and t + 1, in unit of m/s;

a_t is the acceleration in a unit of m/s^2;

g is the acceleration due to gravity, which is 9.8 m/s^2;

$sin\ \theta$ is the road grade, which is assumed to be 0 where roads are generally flat; A, B, and C are road load coefficients, representing rolling resistance, rotational resistance, and aerodynamic drag, in units of kW s/m, kW s^2/m^2, and kW s^3/m^3, respectively; and m is the vehicle weight, in unit of metric ton. For the BJ taxi, it belongs to LDVs, the recommended values of A, B, C, and m are 0.156461, 0.0020002, 0.000493, and 1.4788 respectively [19].

Studies have been conducted to first define VSP bins by operating modes in different operating conditions, and after setting VSP bins, the values of VSP can be one-to-one corresponded and categorized with the bins, so as to statistically analyze the overall VSP distribution as a function of the average vehicle speed. Among them, Op Mode Bins is a classification method for judging vehicle driving behavior based on instantaneous speed and vehicle VSP display characteristics, which has significant features in analyzing the overall vehicle emission characteristics [20]. In this study, Op Mode was used to describe, analyze, and calculate the emission factors of MOVESs operating conditions. Moreover, the VSP fixed interval distribution with split-stroke speed intervals is used for the operating condition characterization. Table 2 shows a concrete representation of the various operating modes provided by MOVES [10] species, which converts the operating modes of different IDs into operating mode bins through vehicle acceleration and deceleration, idling and at different levels of VSP and speed. The operating modes are classified by delimiting different speed intervals, which specifically seem to be divided into three gradients, speed less than or equal to 25 km/h, speed located between 25 km/h and 50 km/h, and speed greater than 50 km/h.

Table 2. Definition of MOVES operating mode characteristics.

Description		Operating Mode (VSP Bin) ID				
Mode Description		**Braking**	**Idling**	**Low Speed Coasting**	**Moderate Speed Coasting**	**High Speed Coasting**
Vehicle Speed, v_t (km/h)		-	[−1.6, 1.6)	[1.6, 40)	[40, 80)	[80, +∞)
Vehicle Acceleration, a_t (m/s^2)		$a_t \leq -0.9$	$a_t > -0.9$	-		
Vehicle Specific Power, VSP_t (kW/tons)	(−∞, 0)	0	1	11	21	33
	[0, 3)	-		12	22	
	[3, 6)			13	23	
	[6, 9)			14	24	35
	[9, 12)			15	25	
	[12, 18)			16	27	37
	[18, 24)				28	38
	[24, 30)				29	39
	[30, +∞)				30	40

3. Results and Discussion

3.1. VSP Distribution Analysis with Different Years

The characteristics of the facility- and speed-specific VSP distributions are highly consistent temporally (between years) and spatially (in different areas), which has been confirmed [21]. However, it is not clear whether the traffic state remains constant because it can be reflected by the VSP distribution. In other words, it remains to be analyzed whether there are differences in the VSP distribution between years or months. Therefore, this study will use the data collected from existing data to compare the data collected in 2013 and analyze and calculate the correlation using the VSP theory method. In order to improve the data quality, the time gap data and road type field are complemented, and the working condition data of the whole, continuous, and effective second time vehicle is screened. The processed data will attain the vehicle information of each vehicle, as well as key fields such as date, time, latitude, and speed of each car as shown in Figure 3, which is the flow chart of the VSP bin obtained based on VSP theory. In this study, non-expressway is mainly used as the research object. The activity data are divided into pieces of "trajectories", each of which consists of 60 s of continuous speed data. The trajectories are grouped into 60 speed intervals on the non-expressway. VSP is calculated by Equations (2) and (3), and VSP distribution is calculated by the Equations and Threshold value division VSP bin.

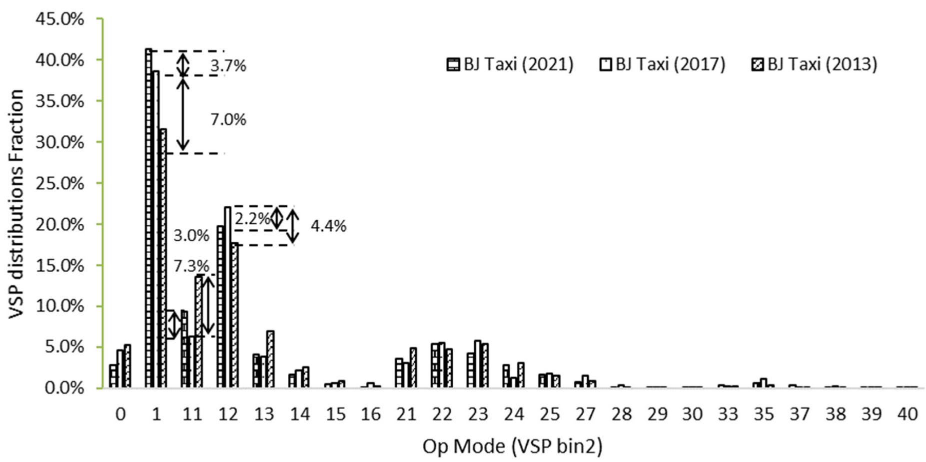

Figure 3. VSP distributions of Op mode ID BJ taxi in 2017 and 2013.

The resulting database includes a broad category of databases.

The statistical database includes the frequency of VSP distribution grouping by road types, average speed, and VSP bin in each vehicle with the information of vehicles.

We chose Pearson's correlation coefficient [22] to describe the trend presented by the VSP distribution and the correlation coefficient of the VSP distribution. The Pearson correlation coefficient is optimized in describing the absolute distance between two points in a multidimensional space with concentrated vector values. Pearson's correlation coefficient is a way to describe the degree of similarity between vectors with a value range of −1 to +1. When the value is taken as 0, it means that there is no correlation between the two, a positive value means that there is the same trend between the two variables, and a negative value means the opposite. The same Pearson correlation coefficient can be applied to study the consistency of the VSP distribution in studies with annual and monthly time granularity, with R_t representing the value sought in Equation (4).

$$R_t = \frac{\sigma\varphi_A\varphi_B}{\sigma\varphi_A\sigma\varphi_B} \tag{4}$$

Therefore, the average correlation coefficient can be expressed as follows:

$$R = \frac{\sum_i R_i}{N}$$

where

φ_A is the fraction in the VSP distribution of A;
φ_B is the fraction in the VSP distribution of B;
$\sigma\varphi_A\varphi_B$ is the covariance of the VSP distribution of A and B;
$\sigma\varphi_A$, $\sigma\varphi_B$ are the standard deviations of the VSP distribution of A and B, respectively;
N is the number of the Pearson correlation coefficients.

The distribution of work conditions under short periods (under monthly changes) is basically unchanged, and specifically, it seems that by performing correlation analysis, it is found that the frequency distribution of each classification is basically more consistent and highly correlated between different months. The result is shown in Table 3. It can be proven that there is high correlation between the five types of classification for months. The mean correlation coefficient of VSP distribution with speed interval is 0.9951 and VSP bin is 0.9892 respectively, which means VSP distribution of month is basically the same as traffic distribution.

Table 3. Mean correlation coefficient of different classifications.

Index	**Classification for Months**		
	Speed Interval	**VSP Bin**	**Speed Interval and VSP Bin**
Mean Correlation Coefficient ($\overline{R}$)	0.9951	0.9961	0.9892

In order to demonstrate the variability of VSP distribution under different long periods, this study found that the VSP distribution of Op Mode in the three years of analysis has a large difference by using data from 2013, 2017, and 2021 for comparative analysis. As shown in Figure 3, the frequency of Op Mode in ID 1 is increasing year by year, 10.7% and 7% higher in 2021 and 2017 compared to 2013, respectively, and 4.4% and 2.2% higher in ID 12 in 2017 compared to 2013 and 2021, respectively, and 3% higher in ID 11 in 2021 compared to 2013. All these changes indicate a more ecological/fuel-efficient driving behavior in 2021 compared to 9 years ago. The more intense driving behavior of rentals in 2013 may be related to elements such as traffic order, civilization, and net-contracting, while the greater proportion of parking hours in 2021 may be related to the concentration of morning and evening peak work under net-contracting competition.

Figure 4 is the distribution of VSP bin under the new sub-average speed interval. From the following figures, it can be seen that the power distribution state of the cab does not change much in 21 and 12 years, and the power distribution is left biased at low speed.

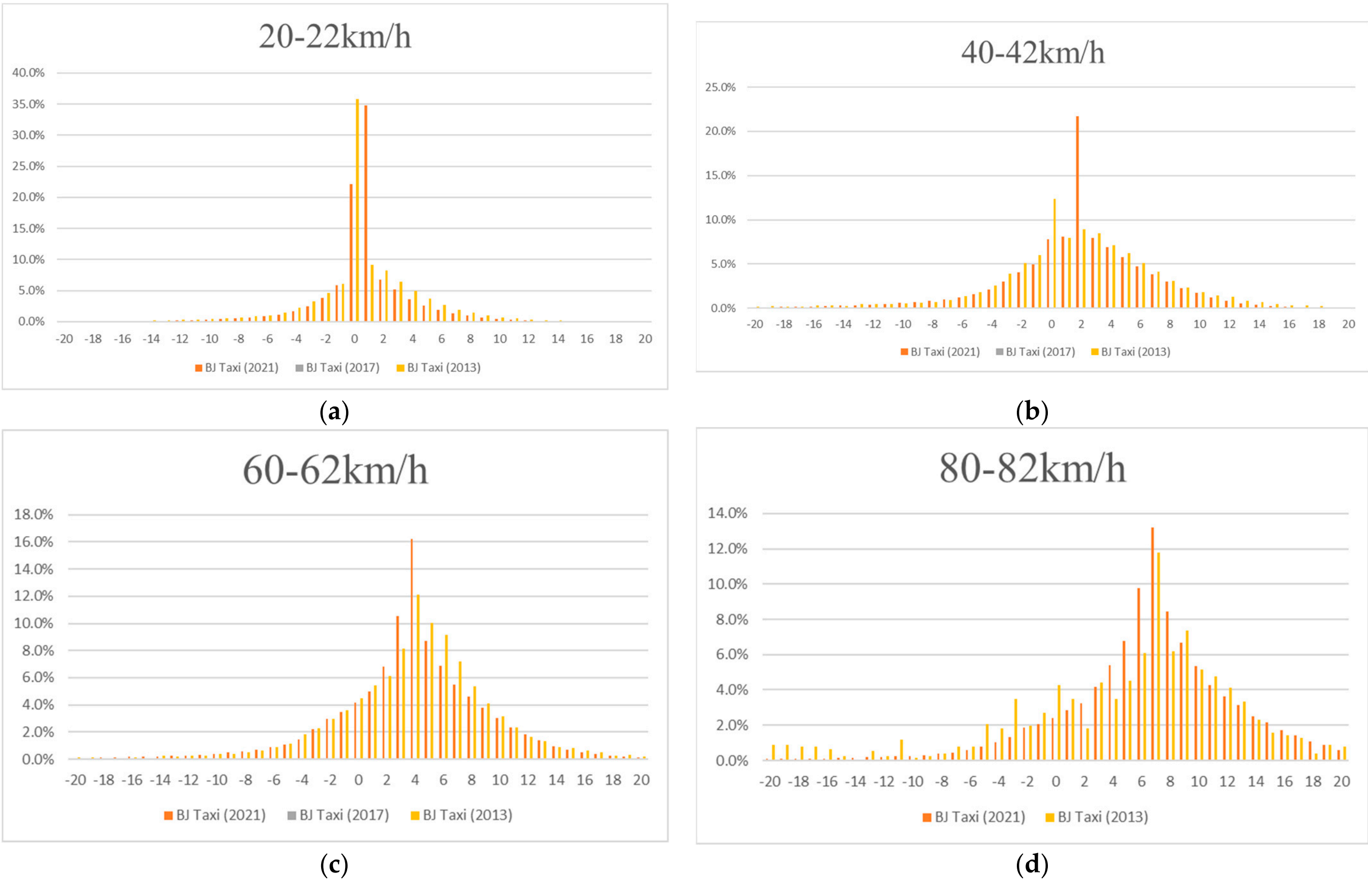

Figure 4. Distribution of VSP bin at the mean velocity interval. (**a**) VSP distributions of Op mode ID BJ taxi between 20 km/h and 22 km/h. (**b**) VSP distributions of Op mode ID BJ taxi between 40 km/h and 42 km/h. (**c**) VSP distributions of Op mode ID BJ taxi between 60 km/h and 62 km/h. (**d**) VSP distributions of Op mode ID BJ taxi between 80 km/h and 82 km/h.

3.2. *VSP Distribution Analysis with Different Cars*

In previous studies [23], limited by the development of information technology, collecting data from car samples was the only way to collect the traffic data of an industry, and the total activity data of all samples were summarized as a representative of the operating mode characteristics. Now, with the innovation of technology, the collected data volume of a single car may be larger than all the data volume collected in a previous survey. Therefore, it can be studied whether the characteristics of a single car can reflect the overall operating mode of the industry and whether it has its own characteristics in the existing technology.

The frequencies of VSP distribution cannot be analyzed as the same bin unit because each VSP interval has its own characteristics. In order to analyze the influencing factors of a single car and all cars to VSP distribution, this paper uses the Coefficient of Variation as the index to measure the uncertainty of VSP distribution. The Coefficient of Variation is the ratio of standard deviation to its mean. When comparing the dispersion degrees of the two sets of data, the Coefficient of Variation can eliminate the influence of measurement scale and dimension. The equation for the consistency of traffic index and velocity distribution is as follows:

$$CV_i = \frac{\sigma_i}{\mu_i} \tag{5}$$

where

CV_i is the Coefficient of Variation of ith VSP bin ID;

σ_i is the standard deviation of the frequency distribution of the ith VSP bin ID;

μ_i is the average of the frequency distributions of the ith VSP bin ID.

The Coefficient of Variation of the data in each operating mode divided by month and car is calculated, and the results are shown in Figure 5. It is found that the Coefficient of Variation in each operating mode divided by month is very low, which is 7.3% on average. The Coefficient of Variation of a single car is 56.8%. Moreover, the Coefficient of Variation in the high-speed interval (Op Mode ID 33, 35, 37, 38, 39, 40) is more than 100%, and in Op Mode ID 40 is even more than 150%. This reveals that the distribution of the operating mode divided by a single car has high uncertainty in high-speed intervals, which also has a significant impact on the results.

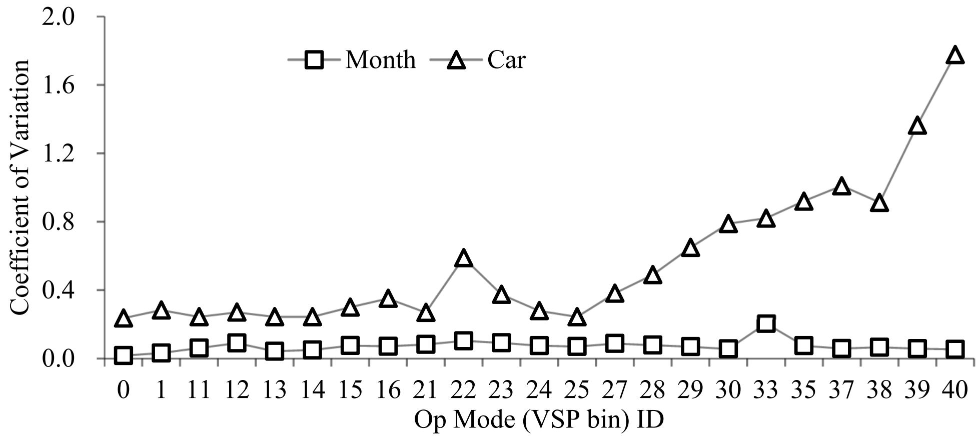

Figure 5. Coefficient of Variation in Op Mode divided by month and car.

3.3. Emission Factors Analysis with Different Cars and Cycles

In order to evaluate the emissions, the speed-specific emission factors of the above operating modes data need to be transformed, which are calculated by using Equation (6).

$$EF_v = 3600 \cdot \frac{1}{v} \sum_i ER_i \cdot VSP\ bin_i \tag{6}$$

where

EF_v is the emission factor in the average speed of v, in the unit of g/km;

v is the average speed in the unit of km/h;

ER_i is the mean emission rate of the ith VSP bin in the unit of g/s;

$VSP\ bin_i$ is the time fraction in the ith VSP bin.

The mean emission rate is a fixed input parameter, in this study, the emission rate of a 2-year-old taxi with China V emission standard will be used. As shown in Figure 6, the final correction data of the mean emission rate is gathered from PEMS test in Beijing taxi.

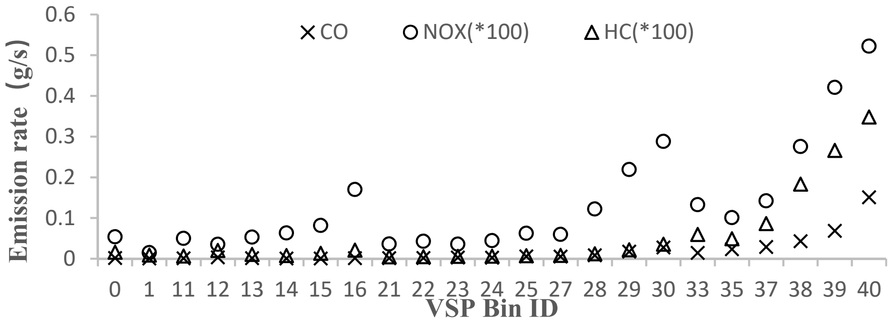

Figure 6. NOx emission rate of two-year-old BJ taxi.

The typical operating modes of each region have the corresponding characteristics. The researchers used four typical light vehicle test cycles compared with the operating modes of BJ Taxi. The New European Driving Cycle (NEDC) is mainly used in Europe, China, Australia, and other countries. Federal Test Procedure 75(FTP75) is mainly used in the United States, Canada, South America, and other countries. Japanese Cycle 08 (JC08) is only used by Japan. The worldwide harmonized Light duty driving Test Cycle (WLTC) is developed by the UN ECE GRPE, which is the newest test cycle for Euro6. The typical operating modes are calculated in accordance with the division mode of VSPbin, and the results are obtained as shown in Figure 7. It can be seen that each typical operating modes and the operating mode of Beijing taxi vary greatly. Namely, the characteristics of each operating mode are very different, which reflects that there may be a large difference in the emissions.

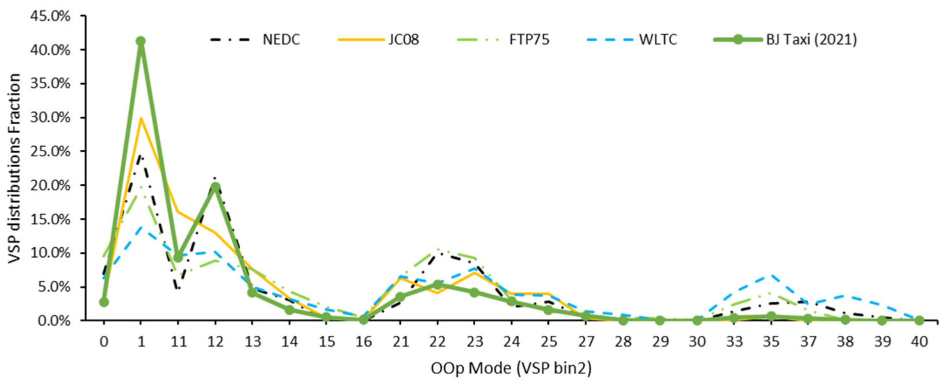

Figure 7. VSP distributions of typical driving cycle.

In order to analyze the emission factor of different driving cycles, this study developed an emission factor curve with the average speed of BJ taxi, and the emission factors of cars and the emission factors of typical test cycles are also calculated according to the above equations. As shown in Figure 8, the correlation coefficients of regression curves for BJ taxi NOx emission factors collected by VSP and speed distribution are very high; correlation coefficient reached 0.9963. In addition, the NOx emission factors for each car and comprehensive taxi industry also have a nice distribution which is distributed around the regression curves for BJ taxi emission factors. The different emission factors are shown in the other four typical test cycles. NEDC and FTP75 are similar to the BJ taxi emission factors, but JC08 is less emission factor than BJ taxi, and WLTC is more emissions in the same test-cycles.

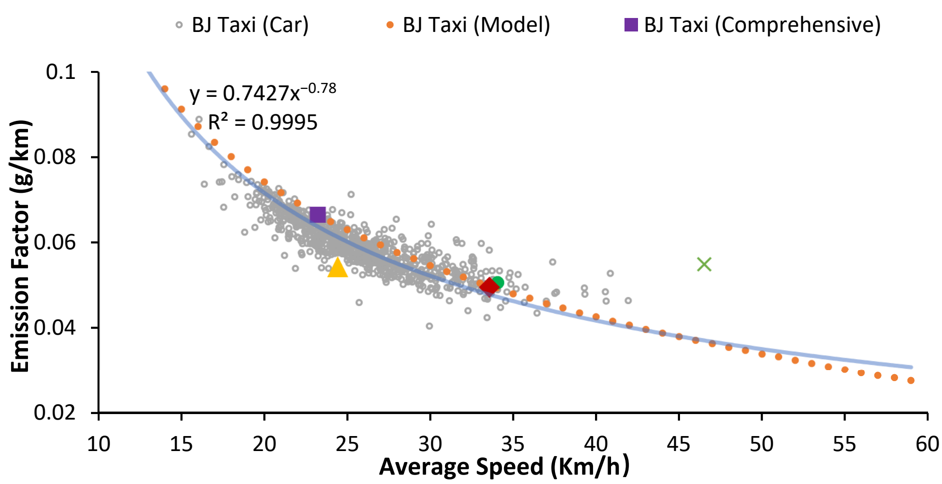

Figure 8. NOx emission factors of average speed, single car, and correction curve in BJ taxi and typical driving cycles.

Based on the above situation, the researchers counted CO, HC, and NO_X emission factor situations in different cycles. The final statistical results are shown in Table 4. The description of the speed-idle ratio is mainly to reflect the actual working condition, the speed is lower than the typical working condition, and the idle ratio is higher than the typical working condition. The emission factors of NOx and HC are often underestimated in the typical operating modes, NOx emission factors in JC08, FTP75, WLTC, and NEDC are 17%, 23%, 17%, and 25% less than BJ Taxi cycle, and HC emission factor in JC08, FTP75, WLTC, and NEDC are 38%, 37%, 3% and 17% less than BJ Taxi cycle. That is to say, the emissions on the real road cannot be reflected well. However, the emissions of CO are overvalued sometimes. CO emission factors in WLTC and NEDC are 37% and 4% more than BJ Taxi cycle. To sum up, the operating modes cannot represent the actual characteristics. Therefore, when conducting a traffic emission assessment, the emission characteristics of the local conditions should be used.

Table 4. Variation of emission factor in different cycles compared with BJ taxi.

Cycles	Cycles Information		Emission Factor (g/km)			Compared with BJ Real-World		
	Speed (km/h)	Idle Fraction (%)	NOx	CO	HC	NOx	CO	HC
JC08	24.4	29.7	0.054	0.28	0.014	−11%	−27%	−33%
FTP75	34.1	19.4	0.051	0.37	0.014	−17%	−2%	−32%
WLTC	46.5	13.0	0.055	0.61	0.022	−10%	62%	5%
NEDC	33.6	24.8	0.050	0.46	0.019	−19%	22%	−9%
BJ Taxi	19.2	41.3	0.061	0.38	0.021	0%	0%	0%

4. Conclusions and Recommendations

This study develops and compares the speed specific VSP distributions of a different month, as well as those in a different vehicle in Beijing. Statistical analysis such as CV and RMSE is used to quantify the differences in the VSP distribution. The main findings are summarized as follows:

(i) The study of Beijing indicates that the distributions of the VSP, velocity, and the Op mode at a time interval within the annual level have superior correlations. In addition, driving conditions in 2021 are more eco-friendly; in contrast, the behaviors 10 years ago were more competitive. This is likely because of the improvement of driving customs and digital development.

(ii) With the information development, the acquired data of operating mode distribution can be used for a wider range of purposes. The study in units of cars demonstrates that the operating mode of the car has individual characteristics. The distributions of different cars in the same month are quite different. Despite the amount of data reaching a certain order of magnitude, it still cannot meet the demand for studying characteristics of the industry. However, the data of cars can be used for the evaluation of dynamic emissions of vehicles, such as estimating monthly emissions factors, evaluating the impact of driving behavior on emissions, and so on.
(iii) Although typical operating modes can restrict the emission requirements of new cars in different areas, they cannot reflect the actual road emissions. Namely, such data cannot be used for the evaluation of actual road conditions, such as establishing localized emissions inventories, evaluating traffic policy emissions, and calculating other emissions that are sensitive to local operating modes.

This paper focuses on the short-term and long-term consistency analysis of the VSP distribution of the massive operating modes data collected under the big traffic data in Beijing, and the analysis of the impact of the actual operating modes and the typical operating modes on the evaluation of the emission factors. In 2021, the world has become more ecological/fuel-efficient in terms of driving behavior compared to 9 years ago. There was more intense driving behavior and cabs had a clear competitive orientation in 2013. We speculate that this is probably related to the traffic order, civilization, and net-contracting. Nevertheless, the future needs to explore the impact of the micro-conditions data on the micro-driving situation and study the analysis method of monthly operating mode distribution data and emission factors data. We will further apply it to other models in future research as well.

Author Contributions: Conceptualization, W.H.; Methodology, W.H.; Supervision, Y.C.; Writing—review & editing, L.D., Z.Z. and X.Z. All authors have read and agreed to the published version of the manuscript.

Funding: This research is supported by the Beijing Municipal Science and Technology Project #Z131100004213003 and Key Research and Development Plan "Research on the Causes and Control Technologies of Air Pollution" (Project No. 2016 YFC0201500).

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Written informed consent has been obtained from the patients to publish this paper.

Data Availability Statement: The data presented in this study are available on request from the corresponding author.

Acknowledgments: The authors thank the support of colleagues from Beijing Transport Institute.

Conflicts of Interest: The authors declare no conflict of interest.

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