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Statistical Vehicle Specific Power Profiling for Urban Freeways

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Abstract

Vehicle Specific Power (VSP) is conventionally defined to represent the instantaneous vehicle engine power. It has been widely utilized to reveal the impact of vehicle operating conditions on emission and energy consumption estimates that are dependent upon speed, roadway grade and acceleration or deceleration on the basis of the second-by-second vehicle operation. VSP has hence been incorporated into a key contributing factor in the vehicle emission models including MOVES. To facilitate the preparation of MOVES vehicle operating mode distribution inputs, an enhanced understanding and modeling of VSP distribution versus roadway grade become indispensable. This paper presents a study in which previous studies are extended by deeply investigating the characteristics of VSP distributions and their impacts due to varying freeway grades, as well as time-of-day factors. Afterwards, statistical distribution models with a scope of bins is identified through a goodness of fit testing approach by using the sample data collected from the interstate freeway segments in Cincinnati area. The Global Positioning System (GPS) data were collected at a selected length of 30 km urban freeway for AM, PM and Mid-day periods. The datasets representing the vehicle operating conditions for VSP calculation are then extracted from the GPS trajectory data. The distribution fit modeling results demonstrated that the Wakeby distribution with five parameters dominates the most fitting parameters with the samples. In addition, the speed variation lies behind the time of day differences is also identified to be a contributing factor of urban freeway VSP distribution.

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Keywords: Vehicle Specific Power Distribution; Second-by-second GPS data

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1. Introduction

Second-by-second Global Positioning System (GPS) data provides flexibility in modelling and characterizing vehicle emissions by using recent modeling technique featuring real-time engine power, Vehicle Specific Power (VSP). It has been widely utilized to reveal the impact of vehicle operating conditions on emission and energy consumption estimates that are dependent upon the speed, roadway grade and acceleration or deceleration on the basis of the second-by-second cycles. Modeling wise, the United States Environmental Protection Agency developed MOVES to estimates emissions for mobile sources covering a broad range of pollutants and allows multiple scale analysis such as emission budgeting of State Implementation Plan (SIP) and transportation conformity purposes (U.S. EPA, 2012). In the current MOVES model practice, traffic activity data inputs are eventually converted into VSP distribution for vehicles (i.e., operating mode distribution in the MOVES model (Beardsley, 2011). Thus, it is very critical to recognize the similarities and differences of engine instantaneous power distributions on a given roadway in order to generate an operating mode distribution for MOVES to maximizing its capacity to accurately reflect the emissions of the real-world. Recently, Song et al. (2010) studied VSP distribution among urban restricted access roadways. It is suggested that the distribution of VSP at various speed bins follow normal distribution. Based on this distribution assumption, the mean and standard deviation of VSP are modeled by using regression techniques. A more recent study (Song and Yu, 2011) by the same authors focused on the VSP distributions on the low speed (less than 20 km/h) segments by using the same methodology. VSP distributions for every speed from 1-20 km/h are mapped and the relationship between VSP fraction and the VSP bin number were observed fits a quadratic function. The latest VSP distribution study by Zhao et al. (2012) concluded that normal distribution is most likely the case for travel speed lower than 90 km/h for both Light Duty Vehicles (LDV) and Heavy Duty Vehicles (HDV). Besides, MOVES default operating mode distribution patterns are very similar to their experimental data. Another study by Lai et al. (2012) investigated the VSP based driving cycles of Bus Rapid Transit (BRT), express and regular bus line. Their results show that when the average speed ranges more than 25 km/h, the distribution of VSP may shifts to the right and does not follow the normal distribution. However, majority of the above studies overlooked one of the most critical contributing factors of VSP, grade, which has been assumed to be zero in most of cases. As a result of such an assumption, it is not a realistic representation for freeways located in hilly terrains of urban area. That is, although the data was collected from real-world, it may lack of representativeness to the urban traffic fleet and may not be sufficient enough to characterized emissions based on the so calculated VSP.

A summary of the state-of-the-art VSP profiling study is first presented, followed by a description of the methodology and data source used in this study. Analyzed results are given for the case of urban freeway segments in Cincinnati urban area. Next, sample distribution fitting results for basic freeway segments by time-of-day are then given. Finally, a summary, conclusions, and recommendations for further research are presented.

2. Summary of Existing Studies

VSP derived from second-by-second vehicle activities are of great interests to the on-road emission modeling field. Aside from conventional second-by-second traffic data sources, microscopic simulation outputs can also be utilized to generate VSP distribution and MOVES inputs. Chamberlin et al. (2012) illustrated a detailed procedure of using VISSIM simulation model to derive MOVES operating mode distribution. Lin et al. (2011) proposed a simulation based dynamic traffic assignment model for project level emissions analyses. The operating mode distribution based on VSP distribution is calculated and applied as inputs for MOVES model. Song et al. (2012) pointed out that using conventional approach to calibrate micro-simulation models may not be applicable for vehicle emission estimate. Instead, the use of VSP distribution to calibrate micro-simulation model is more reasonable based on their study. Since it has been proved that there are direct physical interpretation and well statistical relations with on-road vehicle emissions (Nam and Giannelli, 2005), the distribution characteristics of VSP have been studied. Younglove et al. (2005) investigated VSP distributions for five driving cycles from mild to aggressive. VSP distributions were given and emission rates were also calculated and compared with the binned VSP by using the CMEM model. Lents et al. (2012) included VSP distribution patterns for Nairobi, Santiago and Sao Paulo in the International Sustainable Systems Research Center (ISSRC) funded handbook of air quality management project. This study determined the driving patters of on-road vehicles and supported the development of the IVE model. Frey et al. (2006) finds significant similarities when speed profiles of different roadway facility types are grouped by average link speed. Specifically, VSP distributions are identified to be very identical at a mean speed of 20 to 30 km/h. Yu et al. (2008) collected GPS and PEMS data on the purpose of establishing correlations between VSP and pollutants. The studies (Zhai et at, 2008. Song and Yu, 2009) show that higher VSP values corresponding to higher emissions of Nitrogen Oxidizes (NOx), Hydro-Carbon (HC), Carbon Monoxide (CO), and Carbon Dioxide (CO_2). However, a investigation on the most contributing factors of VSP, grade, is essential to fill the gap identified above. The grade specific VSP distribution results should allow a closer comprehension of how traffic operations impact the emissions. This paper extends previous work on freeway VSP distribution in twofold: (a) by calculating the second-by-second distances traveled and deriving the freeway grades to be used in the VSP calculation, and (b) by fitting the VSP samples into a specific distribution.

3. Methodology

3.1. Data Collection

To fulfil the objectives, a group of freeway segments from Interstate-71 within the Cincinnati urban area were selected. The total length is approximately 60 km for a round trip. The second-by-second GPS data was collected by CVE 351 class students for measuring travel time reliability purpose originally. Vehicles used in this data collect are completely random without any sampling bias. The data covers AM peak hours from 7:00 AM to 9:00 AM, PM peak hours from 4:30 PM to 6:30 PM and Mid-day from 11:30 AM to 1:30 PM. A total of 38 trips were made from January 24th to April 20th, 2012. For the AM perk hours, 36,503 data points were collected, 27,931 data points for Mid-day and 42,624 for PM peak hours. Almost 110,000 records of data were collected in this study on the 30 km Interstate freeway. A data filter with high horizontal dilution of precision (HDOP) greater than 4 and low number of satellites (NSAT) less than 4 (Gong et al, 2012) was applied to remove invalid data due to any circumstances from blocking of satellite signals. After the filtering, a total of 97,491 valid records were used in calculating the VSP.

3.2. VSP and Binning

The mathematical expression of VSP was first developed by J. L. Jiménez (1999) at the Massachusetts Institute of Technology. It is a mathematical representation of engine load against aerodynamic drag, acceleration, rolling resistance, plus the kinetic and potential energies of the vehicle, all divided by the mass of the vehicle. In practice, a generic set of coefficients values estimating VSP for a typical light duty fleet is applied as a useful basis for characterization (Frey et al, 2006). The VSP values for light duty vehicles are calculated by the following equation:

$$VSP = v \times [1.1a + 9.81 \times grade(\%) + 0.132] + 0.000302 \times v^3 \tag{1}$$

Where:

v = vehicle speed (m/s)
a = vehicle acceleration/deceleration rate (m/s^2)
grade = vehicle vertical rise divided by the horizontal run (%)

The horizontal run is calculated by using the haversine formula. It is a method to calculate the shortest distance over the earth's surface by assuming that the trajectory traveled between two consecutive sets of latitude and longitude is a straight line. The so-called great circle distance between two points remains particularly well-conditioned for numerical computation even at small distances (Movable type Ltd, 2012).

$$a = \sin^2\left(\frac{Lat_{(n+1)} - Lat_n}{2}\right) + \cos(Lat_n) \times \cos(Lat_{n+1}) \sin^2\left(\frac{Long_{(n+1)} - Long_n}{2}\right) \tag{2}$$

$$Run = 2R \times a\tan 2(\sqrt{a}, \sqrt{(1-a)}) \tag{3}$$

Where:
Lat= Latitude, Long= Longitude, R = radius of earth (mean = 6,371 km)

The calculations of grade and VSP are implemented in R, an open source programming language and software environment for statistical computing and graphics. In order to avoid any bias might be incorporated in the binning, the minimum interval of 1 kw/ton is used. By using the smallest bin possible, it can help to draw out the quantitative relations between the VSP distribution and the grade. Previous studies (Song and Yu, 2009. Song et al, 2010. Song and Yu, 2011. Zhao et al, 2012) use VSP range of -20 to 20 kw/ton, it was derived based on the data collected from international urban areas such as Beijing. The MOVES model uses VSP range from less than zero up to 30 plus to capture the VSP on U.S. highways. In this study, 98.32% VSP values are distributed in the range of -30 to 45 kw/ton. That is to say, the range of -30 to 45 kw/ton covers majority of the VSP values in this specific urban freeway. Therefore, the following analysis is performed on the VSP bins from -30 to 45 kw/ton. The binning is described below:

$$\forall : VSP \in [n, n+1], \text{VSP bin} = \text{ n}, \ \left(\text{n is integer from -30 to 45}\right) \tag{4}$$

4. VSP Distribution Fitting and Goodness of Fit Testing

4.1. Freeway Grade Distribution

From equation (2) and (3), the freeway grade was calculated. The samples collected shows that 92.35% grade data falls into the range from -10% and 10%. A total of 92,914 grade data points is obtained. Table 1 shows the distribution of freeway grade distributions at two percent interval. There is merely any data points exist for grade equals to zero. This shows that for VSP based emission and energy consumption modeling, the zero grade is rarely the case for urban interstate freeways in some of the U.S. metropolitan areas.

Table 1. Data distribution over freeway grades

	AM	Percentage	Mid-day	Percentage	PM	Percentage
G>10%	291	0.91%	46	0.20%	313	0.83%
10%≥G>8%	280	0.87%	51	0.22%	253	0.67%
8%≥G>6%	548	1.71%	124	0.54%	538	1.42%
6%≥G>4%	1,327	4.14%	522	2.27%	1,264	3.34%
4%≥G>2%	4,083	12.73%	2,774	12.04%	4,669	12.35%
2%≥G>0%	9,143	28.50%	7,939	34.47%	11,633	30.77%
G=0	0	0	2	0	0	0
0>G≥-2%	9,839	30.67%	8,067	35.02%	12,155	32.15%
-2%>G≥-4%	4,106	12.80%	2,861	12.42%	4,740	12.54%
-4%>G≥-6%	1,282	4.00%	431	1.87%	1,249	3.30%
-6%>G≥-8%	536	1.67%	115	0.50%	453	1.20%
-8%>G≥-10%	303	0.94%	47	0.20%	244	0.65%
G>-10%	340	1.06%	56	0.24%	292	0.77%
Sum	32,078		23,033		37,803	

Total	92,914

Based on the data collected, 90.15% AM, 97.3% Mid-day and 92.01% PM data falls into a grade range of -6% to 6%. Figure 1 shows the distribution of freeway grades for the AM, PM peak and Mid-day with the grade equals zero removed. The distribution is almost perfect bell-curves of normal distribution. Again, the freeway grade falls mostly in the rage of – 6% to 6%. Therefore, the selection of grade bins from -10% to 10% is justified and is a well representation of the real-world condition.

4.2. Candidate Distributions

It was observed that the distribution of VSP among the 12 grade bins is seemingly well presented in the parameters of a normal distribution. However, Q-Q plots suggest that the sample tails are not quite following the normal distribution since they are rarely straight. Besides, obviously, there are peaks in almost all of the histograms. Therefore, it is necessary to make a distribution fitting based on the above observed distribution characteristics of the histograms and Q-Q plots. It was also observed that two types of distributions will fit the data well, namely, Wakeby and Generalized logistic distribution. The Percentile-Percentile (P-P) plots comparing middles of sample distribution and model distribution are made. Afterwards, the goodness of fit testing for each of grade and time specific VSP datasets was determined based on the Kolmogorov-Smirnov (K-S) test.

The probability density function of Wakeby distribution is described as below:

$$f(x;\alpha,\beta,\gamma,\delta,\xi)=\xi+\frac{\alpha}{\beta}(1-(1-x)^{\beta})-\frac{\gamma}{\delta}(1-(1-x)^{-\delta})$$

$$\xi \le x < +\infty \text{ if } \delta \ge 0 \text{ and } \gamma>0, \quad \xi \le \text{x} \le \xi+\frac{\alpha}{\beta}-\frac{\gamma}{\delta} \text{ if } \delta<0 \text{ or } \gamma=0 \tag{5}$$

Where: β,γ and δ are shape parameters, ξ and α are location parameters, \

The probability density function of generalized logistic distribution is described as below:

$$f(x;k,\sigma,\mu)=\begin{cases}\dfrac{(1+kz)^{-1-\frac{1}{k}}}{\sigma(1+(1+kz)^{-\frac{1}{k}})^2} & 1+\text{k}\dfrac{(x-\mu)}{\sigma}>0 \quad \text{for k} \neq 0\\ \dfrac{\exp(-z)}{\sigma(1+\exp(-z))^2} & -\infty<\text{x}<+\infty \quad \text{for k=0}\end{cases} \tag{6}$$

Where: $z=\dfrac{x-\mu}{\sigma}$, k is the shape parameter, σ is the scale parameter (σ>0), μ is the location parameter.

To eliminate any bias brought from the negative values of the VSP. A linear transformation was performed so that the sample distributions have a range of positive values yet the distributions remain unchanged.

$$VSP_t = Abs[Min(VSP)] + VSP_x \tag{7}$$

Where: VSPt is the transformed VSP and VSPx is the original VSP value.

4.3. Parameter Estimation

The method of maximum likelihood is a very popular tool in statistical inference to estimate parameters. Basically, it is an iterative procedure to maximize the likelihood of a set of parameter values from the probability model is equal to some observed outcomes. The values of sets of parameter that maximize the sample likelihood are called Maximum Likelihood Estimates (MLE). The function is defined as:

$$L(x_1, x_2, ...x_n, \theta) = \prod_{i=1}^{n} f(x_i, \theta) \tag{8}$$

MLE considered as a function of θ, is called the likelihood function.

4.4. Goodness of Fit Testing

The Kolmogorov–Smirnov (K-S) statistic quantifies a distance between the empirical distribution function of the sample and the cumulative distribution function of the reference distribution. The null hypothesis is that the data follows a specified distribution, and the alternative hypothesis is the data do not follow the specified distribution. The K–S test statistic of a given CDF is defined as:

$$D_n = \max(F_n(x_i) - \frac{i-1}{n}, \frac{i}{n} - F(x_i)), \quad 1 \le \mathrm{i} \le \mathrm{n} \tag{9}$$

Where: D_n is known as the K–S distance
n = total number of data points
F(x) = distribution function of the fitted distribution
$F_n(x) = i/n$
i = the cumulative rank of the data point

The goodness of fit testing using the K-S test yield to significance level α=0.05 is than compared within the candidate distributions. The null and the alternative hypotheses are:

- H_0: the data follow the specified distribution;
- H_a: the data do not follow the specified distribution.

The hypothesis regarding the distributional form is rejected at the chosen significance level (α) if the test statistic, D, is greater than the critical value obtained from a table. The fixed values of α (0.01, 0.05 etc.) are generally used to evaluate the null hypothesis (H_0) at various significance levels.

4.5. Statistical Fitting Results

The data subsets built by grade bins and time of day are then been tested for the two candidate distributions. Histograms of the empirical data and fitted curves are compared. In addition, the P-P plots are being added to the same dataset. The P-P plots provide the magnification of differences of sample and model distributions. Consequently, the selection of fitted distribution is based on the comparisons of PDFs, P-P plots and the K-S tests. Figure 1 shows the model PDF over sample histograms together with the P-P plots side-by-side. The first impression is there are peaks for almost every histogram. This can be a very distinguish characteristics of VSP distribution. From the AM GPS data distributions, it was found that the Wakeby distribution fits the samples very good at smaller grades. However, the P-P plots show that the differences between sample and model distribution increase while the grade increases. Figure 2 shows the model PDF over sample histograms together with the P-P plots of the sub dataset. Similar peaks are identified and the Wakeby distribution fits the samples well. However, there are differences at larger grades, especially at greater than 10% and less than -10%. Comparing to the fit from figure 5, more noise was observed on the comparison of histograms and PDF, as well as the P-P plots. This noise maybe introduced by the relevantly large speed variations. Figure 3 is the comparison of histograms and PDFs, P-P plots of mid-day GPS data. These datasets posses the least speed variations, and therefore, maybe stochastic in terms of their distribution characteristics. As expected, the Wakeby distribution was not the best for smaller grades such as 0 to 2%, 2% to 4%, -2% to 0 and -4% to -2% bins. Instead, the generalized logistic distribution fits the data well and the P-P plots are almost perfect straight lines.

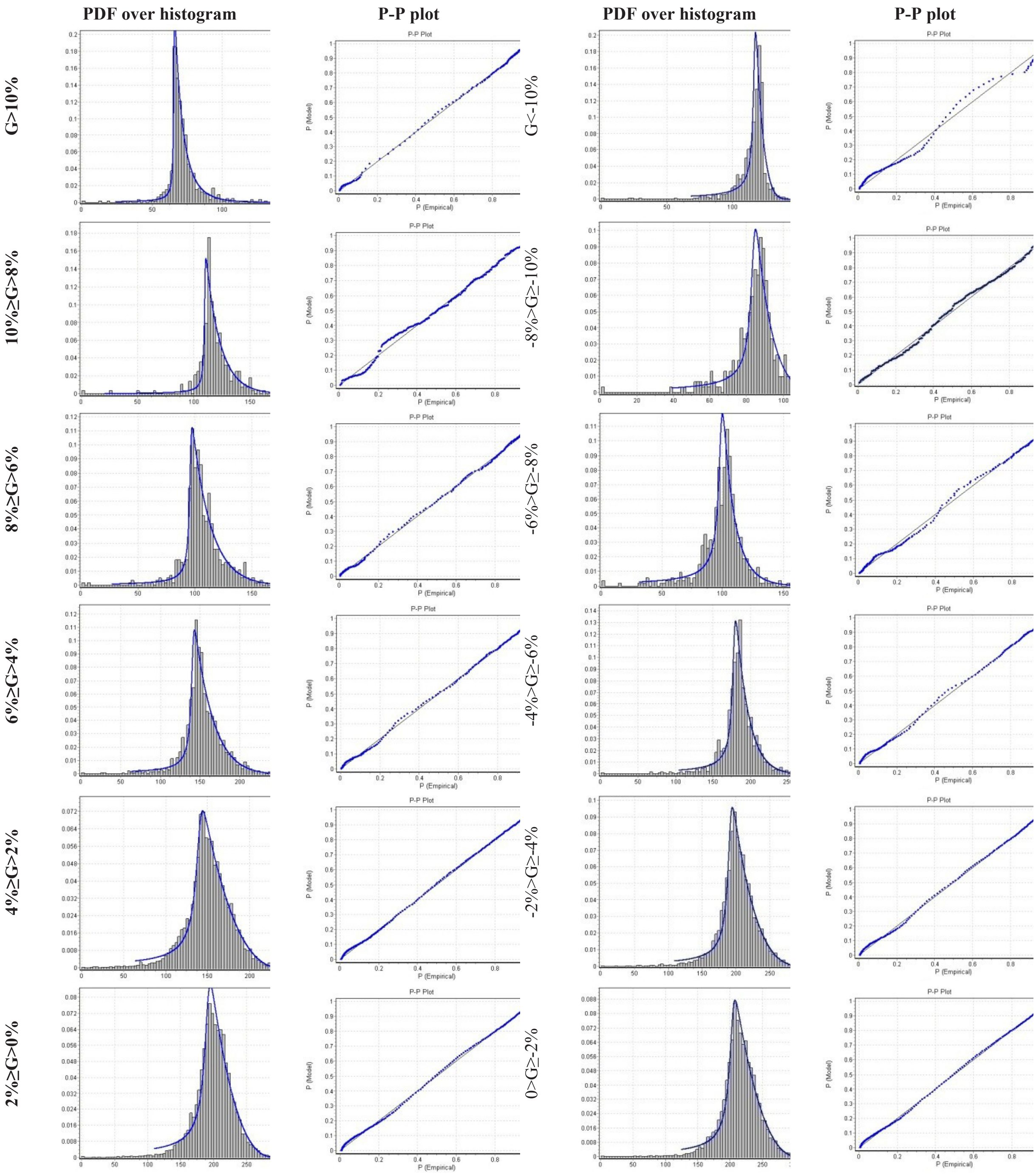

Fig. 1. VSP distribution fitting on AM GPS data by freeway grades

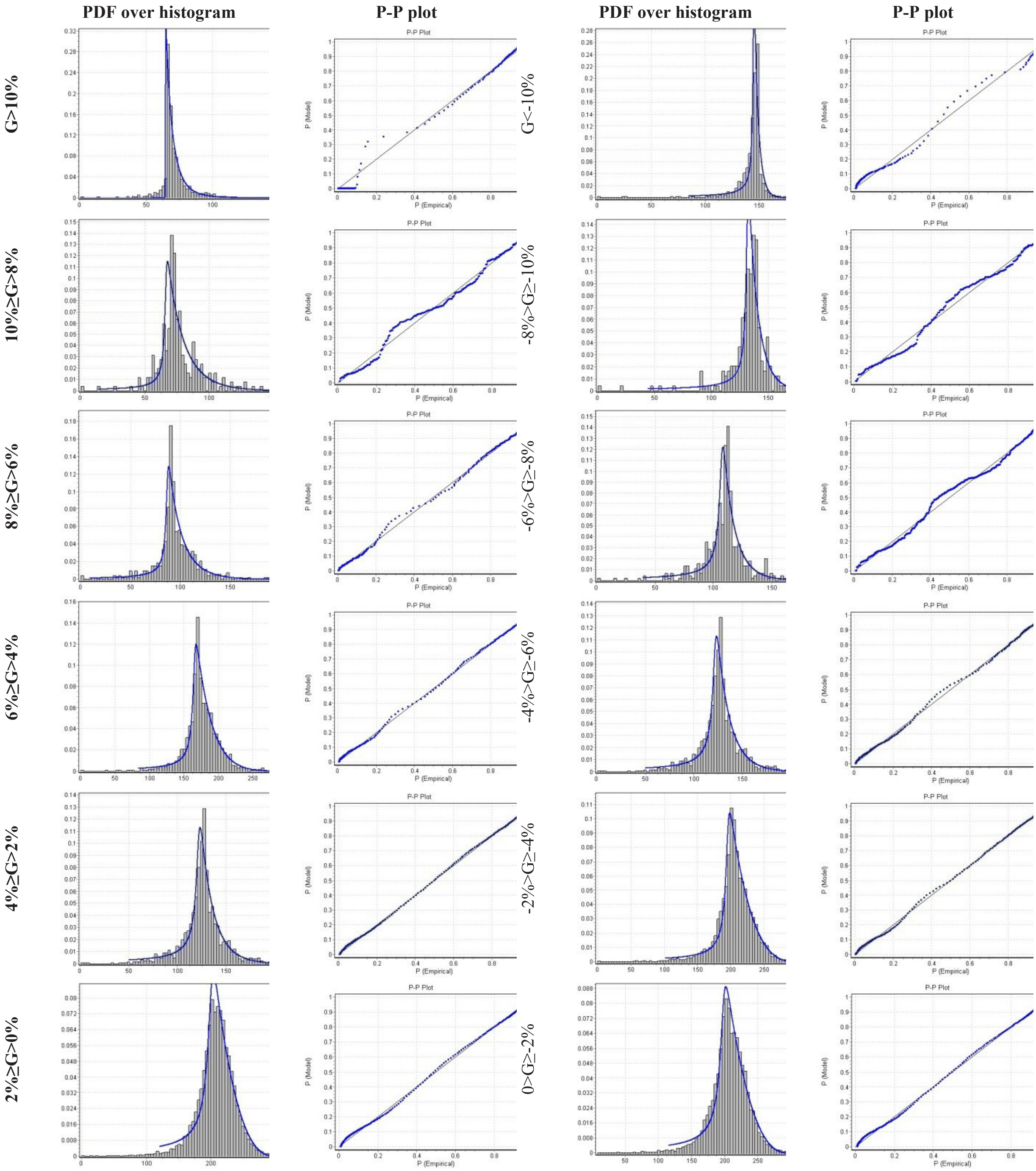

Fig. 2. VSP distributions fitting on PM GPS data by freeway grades

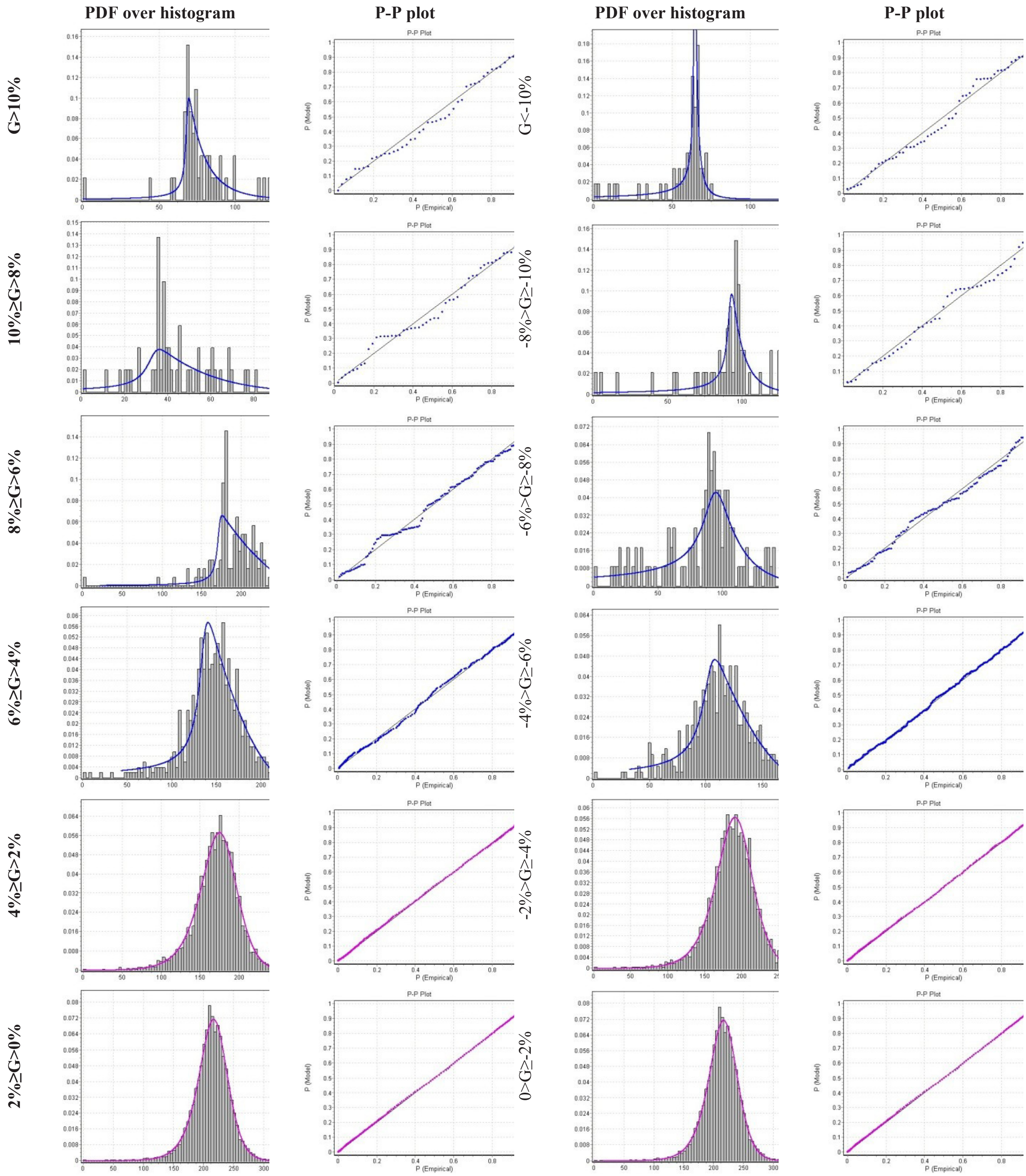

Fig.3. VSP distribution fitting on Mid-day GPS data by freeway grades

Table 2. Fitted distribution parameters for AM GPS data

Grade Bin	Fitted Distribution	Parameter α	β	γ	δ	ζ
G>10%	Wakeby	1812.8	44.495	6.5444	0.21417	23.952
10%≥G>8%	Wakeby	3918.1	45.133	12.632	0.00883	21.087
8%≥G>6%	Wakeby	2049.1	31.133	15.978	-0.02991	27.208
6%≥G>4%	Wakeby	1674.4	23.049	22.612	-0.09393	63.129
4%≥G>2%	Wakeby	953.73	14.211	30.87	-0.2763	63.977
2%≥G>0%	Wakeby	885	12.564	31.094	-0.26791	110.17
0>G≥-2%	Wakeby	971.05	14.091	32.851	-0.28817	125.15
-2%>G≥-4%	Wakeby	1187.4	16.079	28.734	-0.22635	109.55
-4%>G≥-6%	Wakeby	1038.4	15.231	16.855	-0.05051	104.53
-6%>G≥-8%	Wakeby	752.01	11.928	9.6629	0.06215	31.447
-8%>G≥-10%	Wakeby	487.88	11.909	8.3697	-0.12383	39.347
G<-10%	Wakeby	516.33	11.314	5.504	-0.15718	68.561

Table 3.Fitted distribution parameters for PM GPS data

Grade Bin	Fitted Distribution	Parameter α	β	γ	δ	ζ
G>10%	Wakeby	0.075895	3200.8	5.6886	0.22211	-2306.7
10%≥G>8%	Wakeby	1342.6	27.005	12.849	0.08707	14.077
8%≥G>6%	Wakeby	1547.3	20.911	13.403	0.10426	9.4477
6%≥G>4%	Wakeby	1364.9	18.086	21.67	-0.08502	83.809
4%≥G>2%	Wakeby	937.88	13.401	29.947	-0.28075	90.507
2%≥G>0%	Wakeby	822.14	11.995	29.629	-0.26248	121.05
0>G≥-2%	Wakeby	937.78	13.101	30.497	-0.27975	116.21
-2%>G≥-4%	Wakeby	1525.8	17.755	27.359	-0.22625	101.88
-4%>G≥-6%	Wakeby	833.44	12.634	13.092	0.05927	50.451
-6%>G≥-8%	Wakeby	793.26	12.554	9.6325	0.09337	39.697
-8%>G≥-10%	Wakeby	1409.2	16.678	8.3519	0.04483	44.111
G<-10%	Wakeby	790.79	13.665	3.8439	0.01387	84.91

Table 4. Fitted distribution parameters for Mid-day GPS data

Grade Bin	Fitted Distribution	Parameter α (k)	β(σ)	γ(μ)	δ	ζ
G>10%	Wakeby	1655.2	25.157	11.719	0.18276	0
10%≥G>8%	Wakeby	411.8	14.837	22.749	-0.15493	0
8%≥G>6%	Wakeby	4743.4	33.299	43.291	-0.3666	22.441
6%≥G>4%	Wakeby	1098.3	13.502	37.029	-0.35367	42.907
4%≥G>2%	Generalized Logistic	-0.08148	15.335	172.4	N/A	N/A
2%≥G>0%	Generalized Logistic	-0.07578	15.381	242.37	N/A	N/A
0>G≥-2%	Generalized Logistic	-0.0647	15.894	214.5	N/A	N/A
-2%>G≥-4%	Generalized Logistic	-0.06568	16.251	188.96	N/A	N/A
-4%>G≥-6%	Wakeby	635.37	10.769	33.99	-0.35385	32.237
-6%>G≥-8%	Wakeby	511.49	6.0815	18.052	0.02404	-3.2467
-8%>G≥-10%	Wakeby	1292	10.956	7.679	0.20033	-30.193
G<-10%	Wakeby	678.85	8.4462	1.1275	0.64534	-17.055

K-S test results show that all of the null hypothesis, which is the samples follow a specific distribution, are accepted. The corresponding parameters of the AM, PM and Mid-day datasets are listed in table 2, 3 and 4.

5. Summary and Conclusions

This research explores an approach to incorporate freeway grade into the current VSP profiling study. By fitting the samples into a specific distribution function, it is expected to use the function to determine the MOVES operating mode distribution empirically for the purpose of emission and energy consumption modeling. The initial investigation on the freeway VSP distribution by grade bins and time of day demonstrated that there are significant influences from the variations in traffic speed. Consequently, this variation might be a contributing factor that distinguishing the distributions of AM, PM and Mid-day samples. In addition, the sample histograms and Q-Q plots by grades showed the agreement with characteristics of normal distribution. However, it was observed that a peak exists for almost all of the histograms and therefore, the sample distribution need to be further investigated.

Analysis of the statistical fitting of the samples by grade bins and time of day shows that the wakeby distribution dominates the distribution of the VSP. However, for the mid-day samples, where speed variation is relevant small comparing to AM and PM peak hours, generalized logistic distribution fits better for grades between -4% and 4%. K-S tests indicate that the null hypothesis where the VSP distribution follows the wakeby and generalized logistic is accepted for all of the grade bins and time of day. The parameter estimation finds all parameters for the fitted distributions and the results are summarized into tables as described earlier.

The findings of this research can be summarized into the following:

1. Freeway grade does play an important role in VSP profiling. The study has demonstrated that the VSP distribution characteristics differ from one grade bin to another.
2. The sample distribution of VSP can be better modeled at lower grade bins such as -4% to 4%. As the grade increases or decrease to a larger number, the goodness of fit tends to decline.
3. Wakeby distribution was identified to capture majority of the distribution characteristics of VSP at all grade bins. However, when less speed variation presents, the generalized logistic distribution fits the sample data better at smaller grade bins.
4. It appears speed variation plays an important role in the VSP distribution. Smaller speed variation corresponds to better traffic flow leads to a more randomized distribution. On the other hand, larger speed variation corresponds to congested traffic flow leads to an easier modeled distribution.

The focus on the freeway grade and time of day specific VSP profiling and distribution fitting demonstrated that there is a strong connections between VSP distribution and freeway grade. The results further proved that the VSP distribution has a very unique characteristic when the grade is included in the calculation. In addition, the freeway grade calculated from second-by-second traffic operation data, has a significant impact on the VSP distribution and further, the operating mode distribution. The current practice in mobile source emissions modeling suggests that using second-by-second vehicle operation data to create an accurate estimate of emissions for the transportation network is critical. Therefore, better understanding and profiling of vehicle dynamics data (i.e. the VSP distribution), will eventually lead to a more accurate modeling result. The findings also provide a better integration of microscopic simulation and emission modeling. More specifically, it provides a good reference for preparing operating mode distribution inputs for the MOVES model since the distribution function can be used to generate and validate simulation results. For future study, it would be interesting to investigate the grade-specific VSP distributions for roadway other than freeways, such as arterials and locals. In addition, the availability of simultaneous emission data can be a great improvement of the study. The grade-specific VSP distribution correlates to the emission rates would be another contribution to the realm of emission and energy consumption modeling.

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