

An Exploration of CO₂ Emission Models for Horizontal Curves on Freeways

Boya You, Fengxiang Qiao* and Lei Yu

Innovative Transportation Research Institute, Texas Southern University, Houston, Texas 77004, USA

Abstract

Global climate change attributed by CO₂ emissions could seriously impact people's daily lives. According to the statistics, road transport is one of the largest contributors to greenhouse gases. Simultaneously, the increasing number of vehicles, especially vehicle mileages traveled, will continue to induce more CO₂ emissions. It is believed that the driving behavior is one of the most important factors that impact the CO₂ emissions. However, some other factors may also contribute to the CO₂ emissions, for instance, the geometric elements of a roadway. This paper explores the relationship between the horizontal curve radius and CO₂ emissions on freeways from field tests under real-world driving conditions through the development of an Emission Factor Model (EFM). The prediction results were also compared with the measured CO₂ emissions based on the default emission rates generated from Motor Vehicle Emission Simulator (MOVES). The modeling results indicate that the EFM has better performance for the estimation of CO₂ emissions factors for horizontal curves on freeways under free flow conditions with a predicting error of 5.5%, which is much smaller than the one from a method directly estimated from MOVES (16.8%).

Keywords: CO₂ emissions; Emission factor model; Freeway; Horizontal curve radius; MOVES

Introduction

Background

Climate change attributed by Greenhouse Gas (GHG) emissions could impact human's daily lives in a variety of ways. For example, the climate change enhances glacier melting and extends the length of the melt season, which increase river runoff and discharge peaks. The increased runoff could affect the quantity and quality of fresh water sources, thus affecting agriculture, industry, transportation, urbanization, and many other aspects. This would eventually affect the public health [1-3]. Carbon dioxide (CO₂) is the primary greenhouse gas [4], and mostly produced by human activities, such as industries, agriculture, and transportation. In 2012, transportation sector contributed 28% of US total GHG emissions. Within this sector, light-duty vehicles including passenger cars and light-duty trucks were the largest contributors with a percentage of 62% [1]. Meanwhile, many studies have demonstrated that vehicle emissions are sensitive to traffic operations [5] and drivers' driving behaviors [6,7]. Some strategies have been applied to address the vehicle emissions such as charging for CO₂ emissions and promoting public transportation, applying intelligent transportation systems (ITS) to improve drivers' driving behaviors, and so on [8-10]. However, there are always some restrictions to implement those strategies in practice. For example, urban sprawl may weaken the promotion of transit development and application; and it still take time before all vehicles on roads are equipped with ITS for emission reduction purpose. Charging emission by raising gasoline prices may only lead to a small decline in vehicle mileages traveled (VMT) [2]. To effectively reduce the amount of CO₂ emissions, the main focus of attention should be paid to the strategies dealing with the source of emissions. Facts released by the US Environmental Protection Agency's (EPA) show that, road transport is one of the largest contributors to GHG emissions. To estimate vehicle emissions, many mathematical models at macroscopic and microscopic levels have been developed, such as the MOBILE series and MOVES models developed by US EPA, which could be used to estimate the emissions at national, county, and levels. There are two main challenges for emission model development. One is the difficulty in obtaining accurate emission data. Another one is the identification of the structure and parameters of emission models [11-13]. Most emission models, especially the earlier developed models,

focused on the linkages with vehicle speed and acceleration rate [12]. Nevertheless, other factors may also contribute to the vehicle emissions such as the roughness of pavement [14], and the geometric design of roadway [15]. Horizontal curves, which are the segments that provide a gradual change in direction, are important elements in roadway design. Due to the difficulty in judging the sight distance, drivers may apply the brakes or tap the gas pedal frequently when entering the winding segments, which may generate high-frequency accelerations and decelerations associated with extra vehicle emissions. According to the Geometric Design of Highways and Streets [16], also known as the Green Book, the current roadway alignment design method adopted by United States Federal Highway Administration (FHWA), is based on the concept of design speed, with no direct consideration of the environmental impacts [17].

Objectives

The main objective of this study is to develop an Emission Factor Model (EFM) that could reflect the relationship between CO₂ emissions on freeway and horizontal curve radius using aggregated data from field tests in Houston, Texas, USA. The aggregated data used in the proposed exponential model aims to represent the overall condition for each single curve. This method views each single curve as a unit to reflect the relationship between CO₂ emissions and other independent variables. As a comparison, MOVES was used to also estimate the CO₂ emissions under the same curves based on the recorded instantaneous vehicle speed and acceleration/deceleration rates. The prediction results between the EFM and MOVES method would be finally compared.

*Corresponding author: Fengxiang Qiao, Associate Professor And Co-Director, Innovative Transportation Research Institute, Texas Southern University, Houston, TX 77004, USA, Tel: (713) 313-7009; E-mail: qiao_fg@tsu.edu

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Existing emission models and modeling methodologies

To effectively estimate the vehicle emissions, many emission models have been developed. The EPA released new vehicle emissions modeling tool MOVES replaces the previous series of models MOBILE. MOVES estimates emissions based on a bunch of default values and inputs, such as vehicle types, road types, VMT, vehicle age distribution, mileage accumulation rate provided by users. The 'default' database included in this model reflects emission information for the whole country. Also, MOVES can be used to estimate the vehicle emissions at state, county, and project levels. While MOVES could only be used for estimating the vehicle emission at macro and medium levels, the default value, for example, the emission rates and operation mode bin table from MOVES could be extracted and help researchers to calculate the emissions manually [16,18]. A study conducted by Ko generated the speed file for horizontal curves using the speed prediction model and calculated the vehicle emissions based on the emission rates generated from MOVES [16]. The results from this study indicated that several factors such as the curve radius, the 85th percentile tangent speed, and the instantaneous speed at the middle of the curve could affect the emissions on horizontal curves. Other emission models such as EMFAC focus on a macro level based on mean speed and VMT [19,20]. One drawback of these models is that the estimation may not reflect the real-world emission sufficiently without considering the driving dynamics [13,21]. These cycle-based models cannot be used to evaluate the microscope vehicle emissions [22,23]. In order to estimate the vehicle emissions at a micro level, modal-emissions models have been developed. According to Frey et al., there are basically two ways to develop the modal-emissions models [13]: one is to develop a speed-acceleration matrix to classify the operating mode of vehicles [24]; another way is to develop the modal models based on engine mapping [25]. The Mobile Emission Assessment System (MEASURE) developed by the Georgia Institute of Technology is able to estimate CO, NO_x, and VOC_s using aggregated modal modeling approach [26]. Another modal model developed by Barth et al., could also predict the vehicle emissions for light-duty vehicles based on a series of vehicle operating modes [27]. In terms of the data sources, some emission models use field test data [14,15,28], which also known as the 'real-world' emissions, while other models were developed based on the dynamometer testing [29,30]. Also, some micro simulation software such as INTEGRATION and CORSIM, could also be used for the estimation of the vehicle emissions based on speed profiles or traffic conditions obtained from the field tests [31].

Existing on-board emission data collection and data processing

The most common way to collect the emission data is to measure the vehicle emissions through laboratory tests using dynamometer [13,32]. The vehicles used for the laboratory tests are normally new vehicles or under good conditions, which is different from the real world traffic where contains composed of vehicles with varying conditions [33]. To develop an emission model to reflect the driving dynamics at micro level, the analysis of real-world emissions and special measurement techniques are needed. The portable emissions measurement system (PEMS) uses such techniques and could be used to measure the second-by-second tailpipe emissions with the record of vehicle activity information at the same time [33]. Some statistical issues of data processing for the on-board emissions data have been indicated in a previous study such as the representativeness of test vehicles [32]. Several recommendations on data synchronization and the identification of missing data for data quality and data analysis can be found in [5].

Extraction of geometric data

In order to ascertain the relationship between geometric features and vehicle emissions, one challenge is how to obtain the geometric information of roadway alignment because the availability of original drawing files has been the Achilles' heel. Some researchers used a GPS-based method to collect data to compute curve radius and the results showed that GPS was able to provide the alignment data accurately [34,35]. Imran et al., conducted a field test with GPS to collect and calculate the geometric features for horizontal curves [35]. Pratt et al., also used a GPS-based method to collect data every 25 feet to calculate the radius and recommended posted speeds for horizontal curves. The GPS-based field test turned out to be time-consuming even it could produce data accurately [34]. Sanders used a GPS/GIS method to extract the geometric features for horizontal curves, where GPS was used to produce the centerlines of roadways and then the curve data were extracted through GIS. Results showed that the GPS/GIS methodology could provide even higher quality data than field-collected tests [36]. Another report in 2013 also adopted the GIS method to extract the geometric features using the embedded tool in GIS called ArcGIS COGO tool [37]. The horizontal curve types can be identified as simple curves, reverse curves, and spiral transition using satellite maps [38,39]. A previous study conducted by Kim et al., successfully extracted the lateral profiles and superelevation through laser scanning technology [40]. In fact, these cross section elements, for instance, the superelevation, are difficult in determining without the drawing files or field measurements. The simplest and most cost effective option is to identify the geometric information using digital maps. So far many approaches have been developed to identify the geometric features for horizontal curves from digital maps. For example, the Google Earth Pro developed by GOOGLE Company could be used for identifying the horizontal curves by fitting the curves with a radius-changeable circle [41]. Most of the applications use the semi-automatic data-extraction algorithm; no available full automatic method has been found. Curve Extension, Curve Finder, and Curve Calculator are all GIS based curve-extraction tools. The Curve Extension and Curve Calculator could only be used for identifying some geometric elements for a single circular curve, while the Curve Finder could be used to extract several curves on a designated route at one time [42]. Compared with the traditional data sources, GIS maps have advantages such as zero-cost, complete roadway data and short data preparation time [43]. One drawback of the GIS method for curve data extraction is the inclusion of tangent sections when the radii are very large. Khan suggested that curves with radius less than 10,000 ft. and greater than 200 ft. could be selected for tests when using the GIS method [44].

Material and Methods

Portable emission measurement system (PEMS)

PEMS can be used as a measurement tool to quantify the real-world emissions and fuel consumption [33]. The whole system has five main components: the dual gas analyzer, the GPS system, the on-board computer, the PM monitor and the engine data obtained [34]. It is able to provide second by second tailpipe emissions and vehicle activity. In the field test, two operators were involved in the installation of PEMS, which took about 20 minutes. To control the data quality from the start, some recommendations for equipment installation, data collection and data analysis for PEMS from a previous study were utilized [5].

Test plan

This study focused on two 'test circles' around downtown Houston. Figure 1A shows the test sites in this study. Site 1 represents the small

circle while site 3 represents the big one (I-610). Each 'circle' was tested for two rounds. Figure 1B indicates the trajectory of tests. The start/end point was at Texas Southern University. The total distance of the test routes is about 140 km. The testing vehicle was a 2004 Subaru Forester and the fuel type was gasoline. The field test was conducted during the time period of 4:30 p.m. – 8:30 p.m., which cover the peak hour and non-peak hour. The driver was instructed to follow the traffic flow in order to obtain natural data of driving behavior.

Site selection

A series of criteria for site choice were defined. As for now, most of the previous studies related to geometric design, especially the horizontal curves, focused on two-lane rural highways [45-47]. This is because the two-lane rural highway has relatively lower traffic volume and less signalized intersections. Further, it could provide a variety of geometric features [48]. However, the freeways could also provide a variety of geometric features. In the meantime, it is able to naturally rule out the effects of intersections by providing continuous driving data. The roughness of pavement may somehow contribute to the vehicle emission, and the vibration of the testing equipment might also affect the accuracy of data [5]. The pavement of freeway might be more even compared to local roads, which could help reduce the impacts of pavement type. Therefore, this paper focuses on freeways in order to provide purer field-testing data, respectively. Considered that vehicle speed would be affected by the amount of traffic on the road, the data also need to cover different traffic conditions including congested and free flow for the variety of speed. The horizontal curve radius is the only geometric feature considered in this model. To identify the relationship between curve radius and emissions, other geometric elements, for

example, lane width should be constant. Also, the roadway longitudinal grade was assumed to be zero.

- Freeway (e.g., I-610 Loop)
- A variety of geometric characteristics (radii)
- Constant geometric elements (lane width, shoulder width, etc.)
- Same advisory speed (60 mph)
- Data availability

Data collection

Vehicle speed, acceleration/deceleration, longitude, latitude, and vehicle emissions (CO₂) were recorded using PEMS, which produced the records for each second. A Google Earth/Micro Station method was used to extract the geometric features for horizontal curves. First, the Google Earth will be used to generate the digital maps of roadways. Second, the maps produced by GPS will be imported into Micro Station. Third, Micro Station will be used to identify the geometric features. This methodology is composed of four steps: (1) identify the tangent segment; (2) identify the P.I. for curves; (3) identify the curves; and (4) measure the curve radius. Figure 2A shows the identification for geometric features for horizontal curves in Micro Station. The curve radius, degree of curvature, and curve type could easily be identified in the digital maps. The spiral transition curve is the segment between the straight section and a curve, which was designed to prevent sudden changes in lateral acceleration Figure 2B. As the transition segment, the spiral curve is hard to be identified and separated from the digital maps when the drawing files are not available. Due to this reason it is assumed that, all curves are simple curves with no spiral transition. In the modeling part, among the geometric features, only the curve radius will be used as the geometric related independent variables (Figure 2).

Data preparation

PEMS provided a bunch of emission-related data including: instantaneous vehicle speed, acceleration/deceleration, latitude, longitude, and CO₂ emissions. The horizontal curve radii need to be determined manually using Google Earth/Micro Station method. After data collection, the first thing is to match two different data sets based on geo-locations. Due to the connection problem, some invalid data may occasionally be produced by PEMS. To ensure the data quality, data screening was conducted to identify errors and remove invalid data. Also, some outliers and unreasonable test data should be removed from the data set (e.g., an acceleration rate higher than 10 m/s².) In this study, the curve based aggregated data were needed for modeling purposes. Therefore, the substantial amount of instant data generated by PEMS need to be aggregated based on each single curve. After aggregation, there will be a set of unique elements (e.g., the average speed for each single curve; and emission factors for a specific curve) assigned to each curve with different radius. There is one thing should be noticed here is that the aggregate process will neglect the detailed driving behavior.

Modeling

After data preparation, the Emission Factor Model was developed. The EFM viewed each single curve as a unit. The emission factor for tangent will be viewed as a baseline in this model. The data including vehicle speed, acceleration/deceleration, and emission factors for CO₂ were aggregated for each single curve. SPSS was used to run this model and a self-compiled MATLAB program was used for validation.

$$EF_C = EF_T \sum \beta_i x_i \quad (1)$$

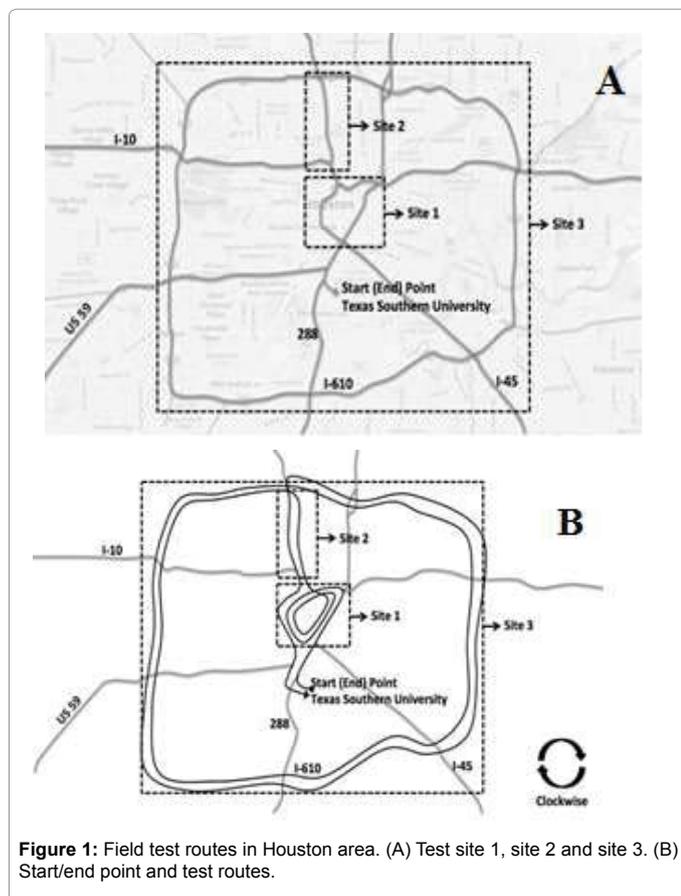


Figure 1: Field test routes in Houston area. (A) Test site 1, site 2 and site 3. (B) Start/end point and test routes.

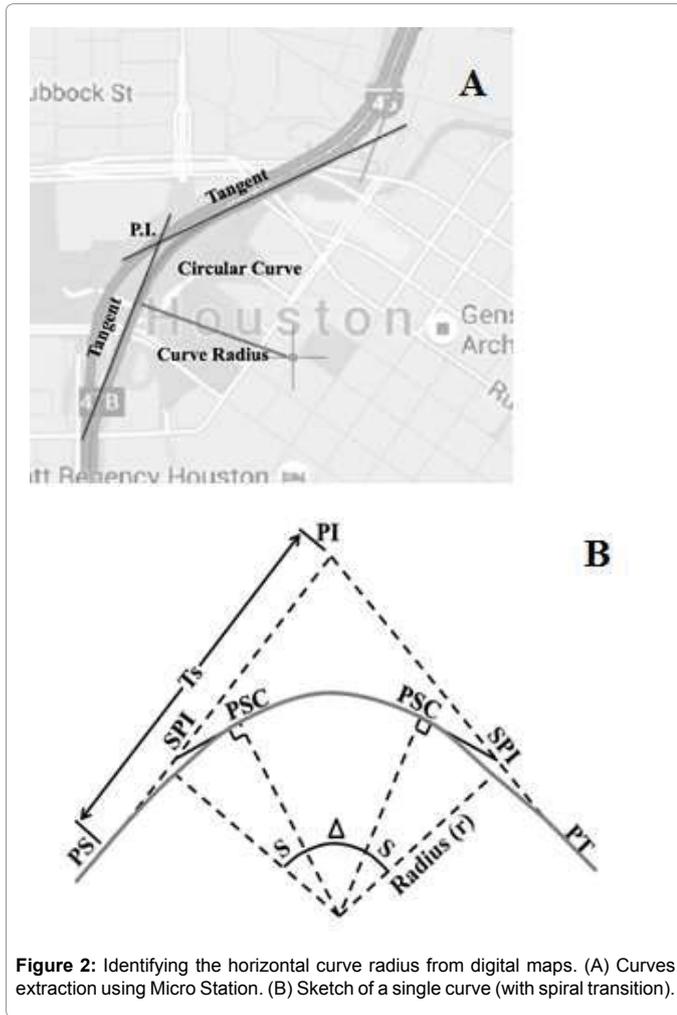


Figure 2: Identifying the horizontal curve radius from digital maps. (A) Curves extraction using Micro Station. (B) Sketch of a single curve (with spiral transition).

$$EF_C = EF_T^{\beta_1 \cdot v + \beta_2 \cdot a + \beta_3 \cdot r} \quad (2)$$

$$\log EF_C = (\beta_1 \cdot v + \beta_2 \cdot a + \beta_3 \cdot r) \cdot \log EF_T \quad (3)$$

$$\frac{\log EF_C}{\log EF_T} = \beta_1 \cdot v + \beta_2 \cdot a + \beta_3 \cdot r \quad (4)$$

Where,

EF_C : emission factor for horizontal curves (g/m)

EF_T : emission factor for tangent segments (g/m)

v : Average vehicle speed for each horizontal curve (km/hr)

a : Average absolute acceleration/deceleration for horizontal curve (m/s²), and

r : Horizontal curve radius (m)

Simulation process using MOVES

In order to compare between the predicting results from EFM and the simulation results from MOVES, the second by second speed file and acceleration/deceleration information were used for calculating the CO₂ based on the default emission rates provided by MOVES. A previous research also estimated the vehicle emissions for horizontal curves of two-lane rural highways using this methodology [16].

First of all, the vehicle specific power (VSP) was calculated based on instantaneous speed, acceleration/deceleration. The equation for VSP calculation:

$$VSP = v * 1.1 * a + 9.81 * \text{grade}(\%) + 0.132v + 0.000302 * v^3 \quad (5)$$

Where v is the instantaneous vehicle speed in the unit of m/s, a is the second-by-second acceleration/deceleration in the unit of m/s². The grade is the roadway longitudinal grade, which could be determined by field measurement or from the roadway profile. In this study, the grade was assumed to be zero. After generating the VSP, the data for each second was assign to a specific operating mode bin provided by MOVES. After matching the operating mode bin for each set of data, the default emission rates were extracted from MOVES's database based on the vehicle type (passenger car), fuel type (gasoline) and the age of the testing vehicle (10 years), and then the accumulated value of CO₂ emissions for each single curve was calculated. The aggregated results (CO₂ emission factor for each single curve) were transformed to Log(EF_C)/Log(EF_T) in order to compare with the results from EFM. The EF_C is the emission factor for each single curve and the EF_T is the average emission factor for tangent segments.

Results and Discussion

Compared to the CO₂ emissions calculated based on the emission rates provided by MOVES, the emission factor model has a better performance to reflect the overall emissions for a single curve using aggregated data. In this session, the results of the EFM will be discussed in detail.

The x-y plot of curve radius and emission factor

After data aggregation, there was one unique set of data for each single curve. For example, when the curve radius is 738.19 m, the average speed for this curve is 67.29 km/hr; the average absolute value of acceleration is 0.376 m/s²; the emission factor of this curve is 2.55 g/m. Figure 3 shows the x-y plotting results. The x-axis represents for the curve radius while the y-axis represents for the value of log (EF_C)/log (EF_T). The plotting results show that when the curve radius is larger, the value of log (EF_C)/log (EF_T) is higher. When the curve radius is approaching 3,000 (estimate), the y-value is approaching 1, which means that the emission factor for curve is close to the emission factor for tangent segment. To explain this tendency, a function was used to fit these data samples:

$$y = \frac{\log EF_C}{\log EF_T} = 1 - e^{-\frac{r}{690}} \quad (6)$$

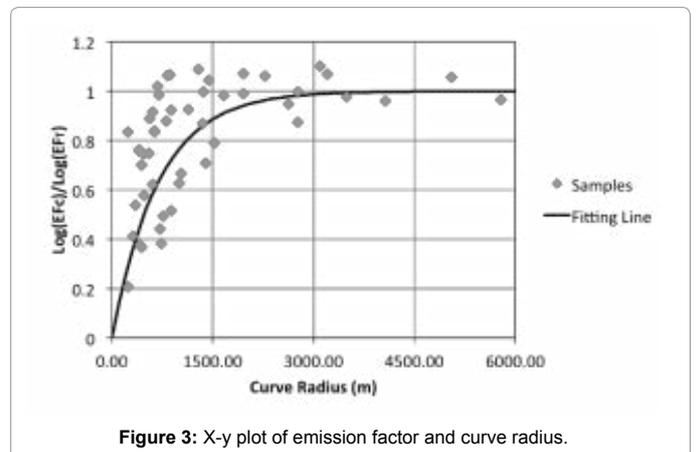


Figure 3: X-y plot of emission factor and curve radius.

Where,

EF_C : emission factor for horizontal curves (g/m)

EF_T : emission factor for tangent segments (g/m), and

r : Horizontal curve radius (m)

When r is zero, y equals to zero. In this case, no roadway exists, then no vehicle emissions. When r goes to infinity, y is 1. Assume that the 'radius' of tangent segment is infinity. When the curve radius goes to infinity, the emission factor for curves will be very close to the emission factor for tangent segment. Also, the yield point of this fitting line is when r equals to 2,070 (2,070 = 690×3, where 690 is a time constant in Equation (6), the 3 times of which means the termination periods of an exponential curve like the one in Figure 3). This means that, when the curve radius is larger than 2,070 m, there is no big difference between emission factors for curves and tangent segments. In order to validate the relationship between curve radius and emission factors, the emission factor models should be developed.

Bubble chart for curve radius, vehicle speed and CO₂ emissions

Figure 4 is the bubble chart showing the relationship between curve radius, vehicle speed, and CO₂ emission. The x-axis represents for the curve radius; the y-axis represents for the vehicle speed and the size of the bubbles represent for the emissions. The bigger the bubble is, the higher the emission is. This chart indicates that the average speed is higher for horizontal curves with larger radius, and also, the emission of CO₂ is higher when the average speed is higher.

Modeling results

The x-y plotting results show that there might be a positive relationship between horizontal curve radius and CO₂ emissions. In order to verify this, a mathematical model in the form of Equation (1) was developed. Table 1 lists the modeling results for the first run in SPSS. The small p-value means the null hypotheses (coefficients=0) should be rejected, which also means that these two independent variables (Curve radius and vehicle speed) have significant impacts on dependent variable (CO₂). Also, the constant is not equal to 0. The

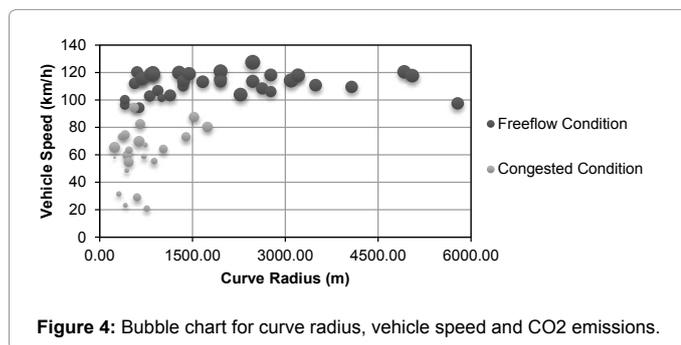


Figure 4: Bubble chart for curve radius, vehicle speed and CO₂ emissions.

Elements	Unstandardized Coefficients 2		t-value	p-value
	B	Std.Error		
(Constant)	0.276	0.082	2.653	0.011
Curve Radius	2.774E-05	0.000	8.452	7.6465E-11
Vehicle Speed	0.006	0.001	2.039	0.047
Acceleration/Deceleration	-0.069	0.127	-0.493	0.625

Table 1: Coefficients for the first run.

p-value for acceleration/deceleration is 0.625 (larger than 0.05), which means the coefficient for the variable of acceleration/deceleration should equal to 0.

Before the second run, the modeling error for each sample was checked in order to screen some outliers. Some extreme sample with a high modeling error was re-examined. For example, the second sample with a curve radius of 241.26 m with a modeling error of 192% was studied and the driving behavior was found to be abnormal within this curve. Driver frequently slammed on the brakes, which may cause the vibration of the equipment and produce some invalid data. The linear regression rerun after deleted the variable of acceleration/deceleration and removed those outliers; the analysis results show in Tables 2 and 3. Table 2 summarized the goodness of fit of this statistical model. The R square is 0.872, which means the linear model fit the data well.

Table 3 shows the final results. Two variables were kept in this model after stepwise regression. The small p-value for Curve Radius (p-value = 0.037 < 0.05) and Vehicle Speed (p-value = 1.006E-13 < 0.05) means that these two variables have significant impacts on CO₂. Also, the rest data samples were used for validation using a MATLAB program. Figure 5A is the plotting for 56 samples. The green line represents for the calculation results from EFM. The black line represents for the real-world CO₂ emissions. The fitting results show that the EFM could well estimate the CO₂ emissions on freeway for horizontal curves. Most points on the blue line, which represents for the calculation results from MOVES, indicate that the MOVES may overestimate the CO₂ emissions on freeway for single curves with different radius. Figure 5B is the estimation error for these two models. The field test data of real-world emission were viewed as baseline with an error of 0. The error-curve radius plotting shows that for both of the model, the error for estimating the CO₂ emission factor is larger when the curve radius is smaller than 1,000 m. This Emission Factor Model covers all the driving conditions including congested conditions and free flow conditions. In order to look into the modeling error, the data under free flow condition and congested condition were separated and analyzed Figures 5C and 5D. The comparison results indicate that this model will produce a smaller error under free flow conditions. The modeling error for EFM under free flow condition was found to be 5.5% while the modeling error under congested condition for EFM was 28%. At the meantime, the modeling error from MOVES was also calculated and the results show that MOVES could estimate the CO₂ emission factor for horizontal curve under free flow condition with an error of 16.8%. The error under congested condition for MOVES is 58.7%. Both of the models have better performance under free flow condition. Figure 6 shows the validation results. The black line represents for the tested value from PEMS. The green line represents for the predicted value calculated by the equation. The blue line represents for the predicting results from MOVES. 10 samples (20%) were used for validation in this study and the prediction error is 4.63% for EMF, which is much smaller than the prediction error produced by MOVES.

The corresponding function is:

$$y = \frac{\log EF_C}{\log EF_T} = 0.006v + (3.213E - 5)r + 0.246 \quad (7)$$

$$EF_C = EF_T^{0.006v + 3.213E - 5r + 0.246} \quad (8)$$

where, EF_C is the predicted emission factor for horizontal curves with different radius, v (km/hr) is the average speed for this single curve; a (m/s²) is the average absolute value of acceleration/deceleration; r (m) is the circular curve radius. The coefficient 3.213E-5 means that, larger

Std. Error of the Estimation	Sample Size	R Square	Independent Variables	Dependent Variable
0.117246012	62	0.872	Curve Radius (m) Vehicle Speed (km/h)	Emission Factor for CO ₂ (g/m)

Table 2: Summary of modeling results.

Elements	Unstandardized Coefficients 2		t-value	p-value
	B	Std.Error		
(Constant)	0.246	0.055	3.784	0.000445
Curve Radius	3.213E-5	0.000	2.148	0.037
Vehicle Speed	0.006	0.001	9.689	1.006E-13

Table 3: Coefficients for the second run.

curve radius will produce more CO₂. The coefficient 0.006 means that the higher the vehicle speeds is, the larger the amount of CO₂ will be.

Conclusion

The modeling results indicate that the curve radius could contribute to the CO₂ emissions. For example, if the average speed for a single curve is constant and equal to 80 km/hr, when the curve radius is 2000 m, the emission factor for curve will be 6.915 g/m. When the curve radius is 4000 m, the emission factor for curve will be 8.099 g/m. Under the free flow condition, according to Ko, the fuel consumption and CO₂ emissions might be reduced due to the speed reduction on sharp curves while larger emissions are related to greater curve radius with tangent speed between 90 and 110 km/hr [16]. Also, the results from previous study also show that the CO₂ emission was minimum within the speed range of 70 to 80 km/hr [49]. The modeling error analysis shows that the EFM has better performance for estimating the CO₂ emission factor for horizontal curves under free flow condition. The predicting error of EFM for free flow condition is 5.5% while the predicting error for MOVES is 16.8%. It is possible that the error under congested condition may be caused by the complex and uncertain driving behavior. Also, the modeling error was smaller when the curve radius is larger than 1000 m. There are mainly two explanations for the error for smaller curve radius: one is that congested traffic flow tends to happen on sharp curves while the model has better performance for free flow; the second explanation is that the error may be generated during the process of extraction for the geometric features from the digital maps. A previous study also suggested that a specific range of curve radius might have better accuracy could be obtained when using the manual extraction methods for horizontal curves from digital maps [44].

The statistical analysis results show that the average speed has bigger impacts on the emission factor for curves with a coefficient of 0.006. The results also indicate that the acceleration and deceleration have no significant impacts on emission factors for horizontal curves on freeway. Under free flow condition, the average speed on freeway is relative high and the drivers tend to apply the brakes or tap the paddles slightly for safety concerns. This may explain why the variable of acceleration has no impact on emission of CO₂ on freeways. Previous studies also stated that the acceleration/deceleration has significant impacts on other vehicle emissions such as CO and NO_x compared to CO₂ [16].

Limitations and Future Work

In this study, the average speed and curve radius were included in the emission factor model, even though the statistical results show that the acceleration/deceleration behavior has no impact on the emission factor for horizontal curves on freeways. The average speed neglected the detailed driving behavior for horizontal curves because of data aggregation. The trips on horizontal curves with different

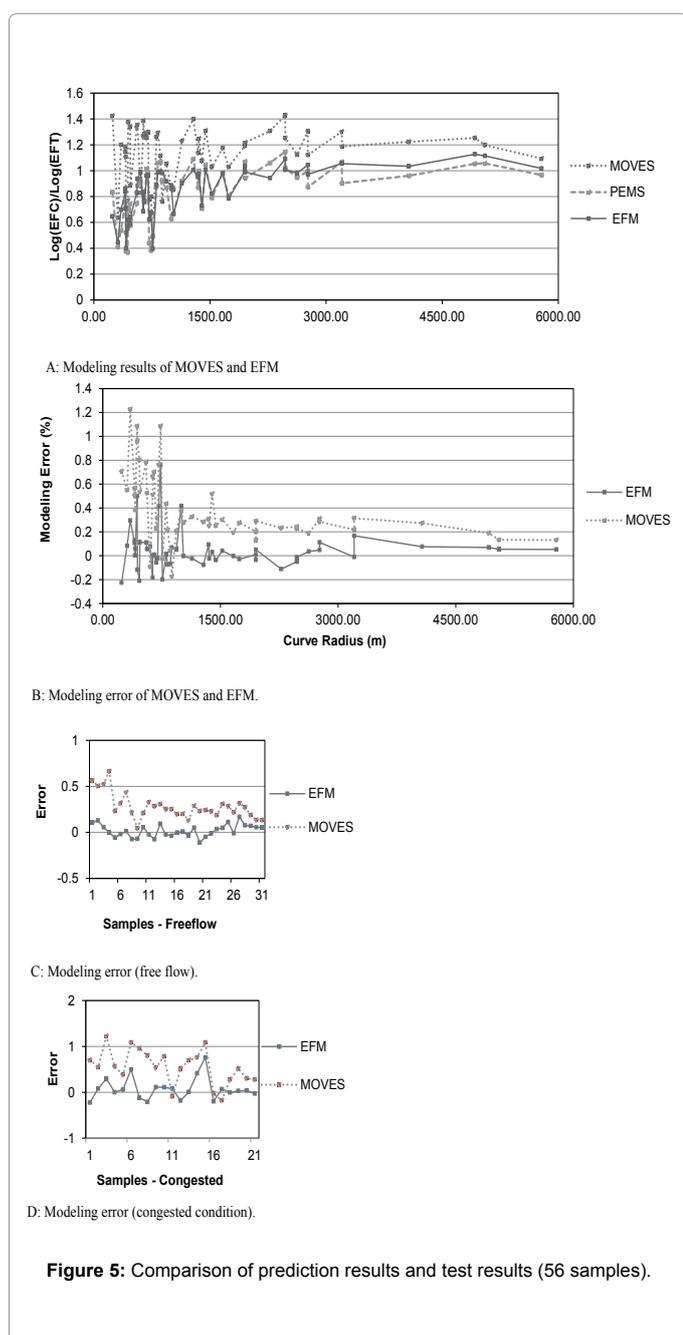


Figure 5: Comparison of prediction results and test results (56 samples).

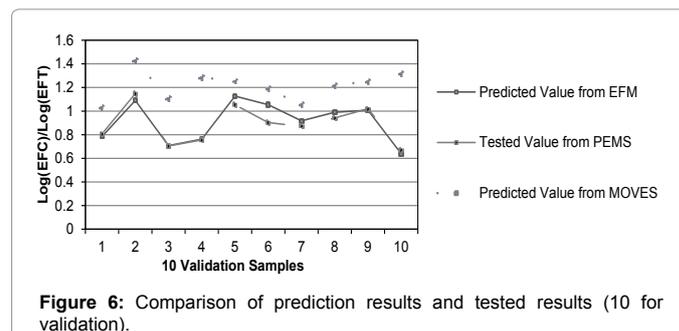


Figure 6: Comparison of prediction results and tested results (10 for validation).

driving behavior may also produce the same average speed. This is one of the major drawbacks in the EFM. After the data aggregation and data screening, the modeling sample size (80% for fitting and 20% for validation) is very limited. All the data from this study were collected from the freeways in Houston area. The EFM could be applied to the freeways with the same pavement type and traffic conditions. Also, in this study, a light-duty vehicle was used for data collection. For estimating the overall CO₂ emission, a factor should be used for the adjustments. There are mainly two assumptions for the horizontal curves in this study: one is that all the curves are simple curves without spiral transition; another assumption is that each curve was viewed as a unit, which neglected the combination of curves. For example, the reverse curves may result in different driving behavior and produce different speed files. As for the future work, more curve-related variables, for instance, the entered-tangent speed will be included in the emission factor model. The modeling results will be linked to the detailed roadway design process.

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