IMPACT OF HORIZONTAL GEOMETRIC DESIGN OF TWO-LANE RURAL ROADS ON VEHICLE CO_2 EMISSIONS

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ABSTRACT

In 2014, highway vehicles accounted for 72.8% of all Greenhouse Gases emissions from transportation in Europe. In the United States (US), emissions follow a similar trend. Although many initiatives try to mitigate emissions by focusing on traffic operations, little is known about the relationship between emissions and road design. It is feasible that some designs may increase average flow speed and reduce accelerations, consequently minimizing emissions.

This study aims to evaluate the impact of road horizontal alignment on CO_2 emissions produced by passenger cars using a new methodology based on naturalistic data collection. Individual continuous speed profiles were collected from actual drivers along eleven two-lane rural road sections that were divided into 29 homogeneous road segments. The CO_2 emission rate for each homogeneous road segment was estimated as the average of CO_2 emission rates of all vehicles driving, estimated by applying the VT-Micro model.

The analysis concluded that CO_2 emission rates increase with the Curvature Change Rate. Smooth road segments normally allowed drivers to reach higher speeds and maintain them with fewer accelerations. Additionally, smother segments required less time to cover the same distance, so emissions per length were lower. It was also observed that low mean speeds produce high CO_2 emission rates and they increase even more on roads with high speed dispersions.

Based on this data, several regression models were calibrated for different vehicle types to estimate CO_2 emissions on a specific road segment. These results could be used to incorporate sustainability principles to highway geometric design.

Keywords: highway geometric design, CO_2 emission, two-lane rural road, traffic operation, environmentally-friendly transport, naturalistic data

1. INTRODUCTION

Carbon dioxide (CO_2) concentrations in the atmosphere have increased significantly over the past century. The 2014 concentration of CO_2 (397 ppm) was approximately 40% higher than that estimated during the mid-1800s, with an average growth of 2 ppm/year in the last ten years. Levels of methane (CH_4) and nitrous dioxide (NO_2) have also significantly increased (International Energy Agency, 2016).

The European Comission (2016) stated that in 2014, Greenhouse Gases (GHG) emissions from transportation represented approximately 23% of the total emissions in the European Union (EU). That year, highway vehicles accounted for 72.8% of all GHG transportation emissions, with about 53% of the CO_2 emissions attributed to inter-urban transportation. Road transportation was also the largest source of nitrogen oxides (NO_x) emissions, accounting for 39% of total EU emissions, and was an important emission source (13%) of fine particulate matter less than or equal to 2.5 microns in diameter (PM2.5). Road transportation can also contribute significantly to the total emissions of other pollutants, such as sulfur oxides (SO_x) and carbon monoxide (CO).

In the United States, emissions from transportation increased by approximately 17% from 1990 to 2014 (US EPA, 2016). The combustion of fossil fuels to transport people and goods is the second largest source of CO_2 emissions, accounting for about 31% of total US CO_2 emissions in 2014. The largest sources were passenger cars (42.4%), medium- and heavy-duty trucks (23.1%), and light-duty trucks (17.8%). The transportation sector is also responsible for 20% of CH_4 emissions and 41% of N_2O emissions from fossil fuel combustion.

In light of this situation, both Europe and the United States have increased their policy measures to address issues concerning air pollution from transport. These policies primarily focus on road pricing and internalization, intelligent transport systems, urban mobility/smart cities, eco-driving courses, and speed limiters. These policies, however, do not include strategies aimed at reducing emission through highway geometric design choice in spite of the fact that this variable can influence vehicle fuel consumption and emissions.

Several models based on vehicle factors have been calibrated to estimate fuel consumption and vehicle emissions. These models are classified into two categories: models for emissions inventory and instantaneous emissions models (Park et al. 2016).

Models for emissions inventory consist of various emission factors which depend on vehicle motor features. An emission factor is normally retrieved from the model database based on several variables such as vehicle age, vehicle class, fuel type, engine technology, model year, facility type, average speed, and pollutant type. The emission factor is multiplied by the traffic activity expressed in kilometers to calculate emissions. All current models use average trip speed as the key input variable, except for the Handbook of Emission Factors for Road Transport (HBEFA) model and the Motor Vehicle Emission Simulator (MOVES) model. The HBEFA model is based on traffic situation, whereas the MOVES model is based on speed and power demand derived from driving patterns and circumstances.

Alternatively, instantaneous emissions models are generally applied in project-level or individual vehicle-level analysis, since they provide more precise spatial and temporal analyses. One example is the VT-Micro model developed by Ahn et al. (2002), a nonlinear regression model which uses a multi-dimensional polynomial model structure to predict vehicle fuel consumption and emissions, using instantaneous speed (km/h) and acceleration (km/h/s) as explanatory variables for light duty vehicles and trucks. The VT-Micro model predicts fuel consumption and emissions with a small margin of error with respect to field data (Rakha et al. 2004). However, some limitations need to be considered when applying this model: 1) the model estimates vehicle emissions for hot stabilized conditions and does not consider the vehicle warm-up effect, and 2) the model is confined to speed and acceleration levels within the data range (speed lower than 121 km/h, and acceleration between -1.5 and 3.7 m/s^2). Additionally, this model classifies vehicles into categories according to their emission characteristics (Rakha et al. 2004): five light duty vehicle levels (LDV) and LDV high emitters, and two light duty truck levels (LDT) and LDT high emitters.

El-Shawarby et al. (2005) validated the model and evaluated the impact of vehicle cruising speed and acceleration levels on vehicle fuel consumption and emission rates from field data. They demonstrated that vehicle fuel consumption rates per distance were the lowest in the range between 60 and 90 km/h. Vehicle cruising speeds outside this range resulted in considerable increases in fuel consumption and emission rates.

The analysis of vehicle acceleration showed that if fuel consumption and emission rates are considered only for acceleration maneuvers, emissions decrease. This is caused by the reduction in the distance and time that are required to execute the acceleration maneuver. However, the results demonstrate that if the emissions data are collected over a sufficiently long distance, the conclusions are reversed (as the level of acceleration increases, the emissions increase).

Although most studies are focused on operational variables, there are some studies that have analyzed the influence of design geometric features on fuel consumption and emission rates. The most studied geometric variable is the longitudinal grade. Boriboonsomsin and Barth (2009) studied the fuel consumption from a vehicle driving along uphill, downhill, and flat routes. The speed was held constant at 60 mph (90 km/h) to control the speed and acceleration variables across all routes. Results showed a parabolic relationship between fuel consumption and longitudinal grade (R^2 of 0.93), meaning that longitudinal grade had a significant effect on the fuel economy of light-duty vehicles. In fact, the vehicle fuel economy of the flat route was approximately 15-20% higher than for the uphill and downhill routes.

Other studies have used the estimation of speeds and accelerations as inputs for emission rate modelling because field data collection can be expensive and difficult to implement. Park and Rakha (2006) used the INTEGRATION microscopic traffic simulation software with three types of traffic control scenarios. This software estimates speeds and accelerations and uses the VT-micro framework to calculate fuel consumption and emission rates. They concluded that longitudinal grade is an important factor in fuel consumption and emissions. For a 1% increase in longitudinal grade, fuel consumption and emission rates increase approximately 9%.

Ko et al. (2013) used the truck dynamic model and non-uniform acceleration/deceleration models for creating second-by-second vehicle speed profiles based on three key factors: grades, initial speeds and critical length of grades. Simulated trips covered longitudinal grades from 0% to 9% (increased by 1%) and initial speed from 10 km/h to 110 km/h (increased by 10 km/h). These estimated speed profiles were the input to estimate fuel consumption and emissions with the MOVES model. The analysis of the outputs showed that faster initial speeds in the longitudinal grade design would reduce fuel consumption and emissions. They also concluded that fuel consumption and emissions on a segment with an upgrade of 9% were four times higher than on a flat segment.

Likewise, the research team also analyzed the design of vertical crest curves (Ko et al., 2012). Second-by-second operating speed profiles were created based on a model with the rate of vertical curvature (K) as an explanatory variable and a polynomial model for acceleration estimations. Like in the previous case, estimated speed profiles were the input for determining fuel consumption and emissions with the MOVES model. The results showed that as K increased the fuel consumption decreased along the vertical curves. The design vehicle consumed about 10% less fuel (and thus produced 10% less CO_2) on a curve designed with a 50% higher K than the minimum standard according to the Green Book (AASHTO, 2011). In addition, 10% more fuel was consumed (CO_2 was produced) for a 50% smaller *K*.

The impact of horizontal curve design on fuel consumption and emission rates was evaluated following a similar procedure (Ko, 2015). In this case, the input for fuel consumption and emissions was estimated with the MOVES model using second-by-second operating speed profiles, based on a model with travel path radius, 85th percentile tangent speed, deflection angle, and superelevation as explanatory variables and a polynomial model for acceleration estimations. The speed profiles were generated under similar conditions (70 km/h tangent speed, 90 degree deflection angle, and 8% superelevation rate) for radii 10-50% lower and higher than the minimum standard horizontal curve radius according to the Green Book (AASTHO, 2011). The design vehicle consumed 34% more fuel and produced up to 91% more emissions for curves with a 50% lower radius than the minimum standard. When the radius was larger than minimum standards, fuel consumption and emissions were slightly lower because of the shorter distance and time. It is important to take into account that in all three studies the authors have assessed fuel consumption and emission rates per trip instead of distance.

In conclusion, many studies have been developed to determine the influence of vertical alignment on GHG emissions, whereas little research has focused on the effects of horizontal alignment. In an attempt to gain insight into the impact of highway geometric design on vehicle fuel consumption and emission rates, this research aimed to study the impact of horizontal highway geometric design on vehicle CO_2 emission rates by applying the VT-Micro model to actual in-field driving data.

2. OBJECTIVES AND HYPOTHESES

The main objective of this study is to analyze how horizontal highway geometric design features influence GHG emissions, specifically CO_2 emissions. The procedure of the analysis is based on actual continuous speed profiles and a microscopic fuel consumption and emission estimation model. The study focused on CO_2 emissions because it is the major contributor to global warming, despite the low impact to human health. Additionally, CO_2 emissions is strongly related to vehicle fuel consumption.

The underlying hypothesis is that highway geometric design has an important impact on fuel consumption and emissions. Road design strongly influences driver operation like speed and accelerations, which can be key factors in emission production. To this end, the lower driver's speed and the higher the speed variations, the higher the emission rates. Therefore, emission rates will likely be lower on two-lane road segments whose horizontal geometric design induces drivers to drive smoothly.

3. METHODOLOGY

Previous studies have analyzed the impact of road geometric design on emission levels from estimated operating speed profiles for different theoretical scenarios. However, methodology applied in this study is based on the application of a microscopic emission estimation model to actual individual second-by-second speed profiles gathered during naturalistic data collection on two-lane rural roads (FIGURE 1).

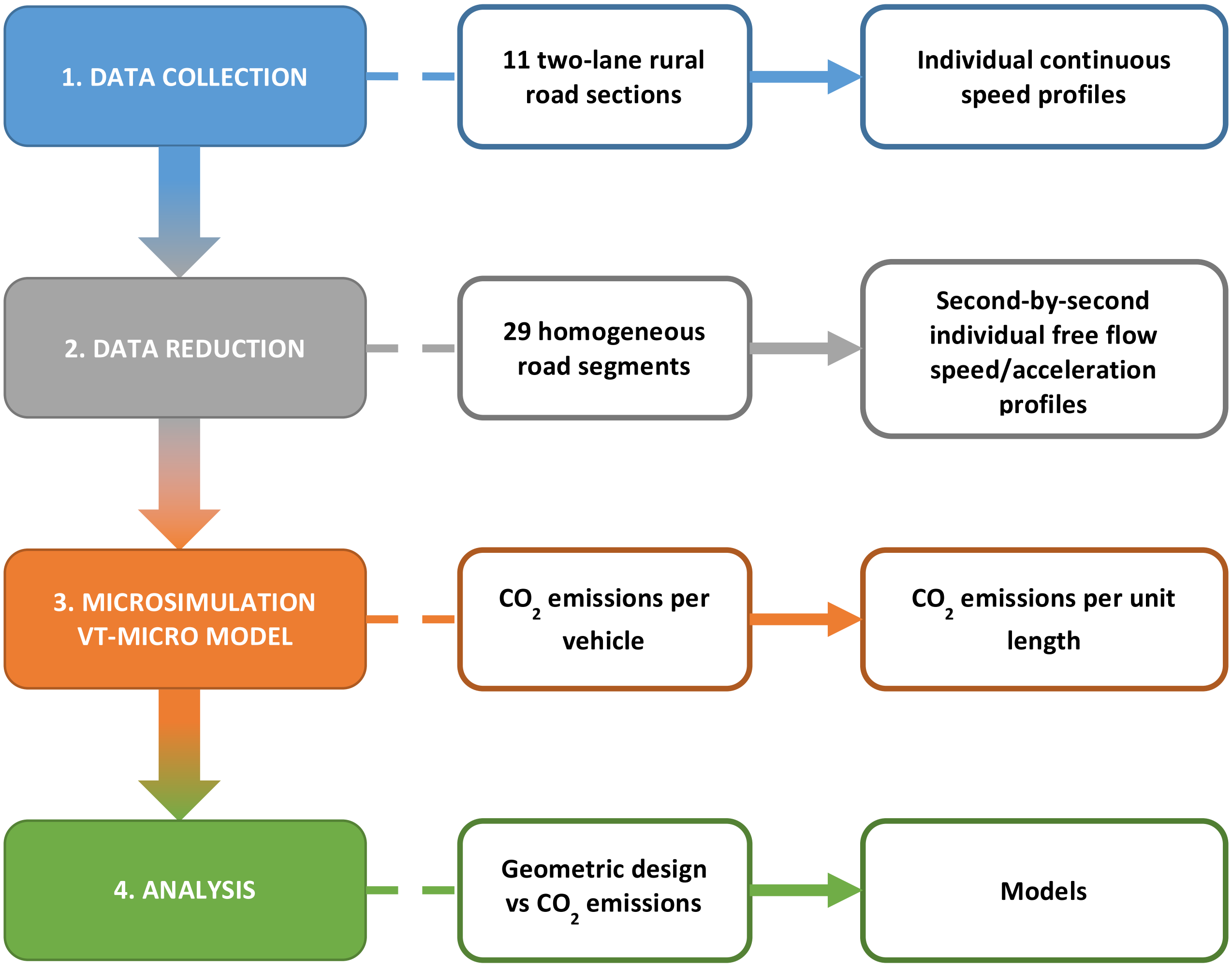

FIGURE 1 Methodological flowchart.

3.1 Data collection

This research is based on a database of more than 16,000 veh-km collected in 2008 on 11 two-lane rural road sections. Speed data were collected on work days between 8:30 a.m. and 2 p.m. and under dry weather conditions. The data collection methodology was developed by Pérez-Zuriaga et al. (2010). The length of the selected road sections ranged from 5 to 20 km, with an estimated Annual Average Daily Traffic (*AADT*) volume between 850 and 7,000 vpd.

The main objective of this research was to analyze how the horizontal alignment affects emissions, since the influence of the vertical alignment is far better known. Thus, the road segments studied presented a nearly flat vertical alignment (Table 1).

TABLE 1 Road Segments Characteristics

ID	L	CCR	AR	R_{max}	R_{min}	$\overline{V}_m$	$\overline{V}_{85}$	$\overline{V}_{50}$	σ_{Vm}	σ_{V85}	σ_{V50}	g(+)	g(-)	d
1.1	2691	19.68	1059	2018	449	88.09	103.34	86.12	6.49	7.18	5.43	3.89	-2.04	73/71
1.2	2689	135.60	192	490	71	79.15	91.17	78.14	5.48	6.82	5.22	4.25	0.00	66/85
1.3	1721	548.76	108	372	40	59.16	67.07	58.97	8.19	10.23	8.01	5.42	0.00	71/86
1.4	2867	151.01	177	480	85	75.87	88.07	75.00	6.46	8.07	6.46	5.23	-5.11	68/75
1.5	2396	0.00	---	---	---	94.88	114.70	91.43	6.44	8.81	5.23	2.04	-2.62	76/78

2.1	2321	317.22	151	610	66	66.57	75.60	65.50	6.39	8.43	6.03	4.08	-0.56	76/65
2.2	1625	138.89	368	749	129	75.08	85.39	74.19	4.17	4.84	4.14	5.32	-4.49	71/65
3.1	1082	220.22	219	502	66	74.01	85.71	73.97	10.79	13.66	10.09	3.79	-2.13	109/125
3.2	2968	59.54	365	808	86	86.01	98.53	84.50	7.60	8.67	6.67	3.04	-3.26	75/113
3.3	3627	172.53	222	447	97	77.60	87.76	76.25	7.57	8.96	7.16	2.10	-2.50	96/121
4.1	1604	0.00	---	---	---	89.91	101.89	87.65	3.16	3.44	2.90	1.38	0.00	85/72
4.2	2833	43.67	1352	2946	247	85.57	95.97	83.83	6.95	8.26	6.39	1.42	0.00	73/68
5.1	1739	80.88	804	2057	254	86.67	97.95	85.79	2.78	3.15	2.89	2.28	-2.24	75/55
5.2	1138	14.03	662	662	662	94.43	105.19	93.65	1.31	1.69	1.15	0.11	-1.53	81/60
5.3	2349	72.65	452	725	260	87.67	98.49	86.91	6.49	7.36	6.14	1.29	-2.43	42/36
6.1	1775	82.90	278	695	86	71.24	80.11	70.38	6.01	6.65	5.88	1.43	-1.23	66/89
6.2	2141	30.78	1042	3210	161	76.76	87.41	75.36	6.72	7.73	6.17	0.81	-2.12	64/89
7.1	2529	157.26	264	685	167	73.60	81.32	73.23	4.22	4.29	4.01	1.97	-0.70	77/61
7.2	1239	9.17	625	625	625	76.97	85.97	76.62	4.84	4.59	4.69	1.90	-2.67	77/61
8.1	4638	20.69	534	963	194	84.61	97.39	82.58	5.01	7.18	5.51	2.55	-1.71	73/66
8.2	2843	59.28	367	884	231	79.19	90.46	77.39	2.46	3.34	2.32	2.89	-1.79	72/70
9.1	1054	42.46	7421	14761	82	73.69	83.22	72.64	9.12	10.35	8.59	0.02	-0.09	85/75
9.2	1529	80.08	412	957	100	72.97	82.41	72.16	6.04	7.48	5.67	0.47	-0.24	72/72
9.3	1915	8.79	505	514	498	78.33	88.75	76.93	3.44	4.11	3.03	0.15	-0.48	71/68
9.4	1128	61.82	404	999	113	67.69	76.45	67.47	2.87	3.24	2.88	0.16	-0.09	77/76
10.1	1832	14.54	480	573	387	87.09	98.38	85.37	3.51	4.63	3.28	0.98	-0.43	51/38
10.2	1702	172.38	230	539	85	72.62	79.28	72.62	5.98	6.73	5.81	2.30	-1.56	41/40
10.3	2457	92.21	265	417	98	75.28	83.40	75.14	4.11	4.77	4.10	3.84	-3.17	34/34
11.1	2930	36.15	302	716	131	74.89	82.61	74.26	5.46	5.98	5.39	0.63	-1.58	26/26

Data collection was carried out by placing two checkpoints at the beginning and at the end of each road section (FIGURE 2). Every incoming vehicle was halted and drivers were asked to participate in the study. If the driver agreed (nearly 90% did), a 1 Hz pocket-sized GPS was placed on the vehicle.

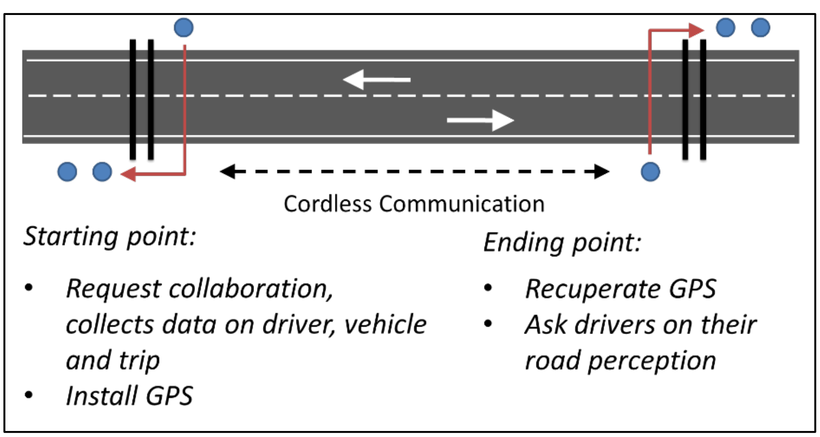

FIGURE 2 Field study.

Furthermore, to check whether drivers were biased because of the presence of the GPS device, a naturalistic test was carried out (Pérez-Zuriaga et al., 2013). The test was based on comparing spot speeds of drivers who were carrying GPS devices and drivers who did not. The speed of the second category was collected a day before the experiment using video cameras. The results validated the methodology, since no statistical difference was found between both data sets.

The results of the data collection were used to develop a database of vehicles location presented in a latitude-longitude-altitude-heading direction-time-date format, at a 1-second pace.

3.2 Data reduction

Collected data were transformed to Universal Transverse Mercator (UTM) coordinates, and were then filtered and processed to obtain individual continuous speed profiles (Pérez-Zuriaga et al., 2010). Free-flow conditions were checked (Pérez-Zuriaga et al., 2013). This was done easily by assuming that every driver tends to adopt the behavior of a specific speed percentile. Thus, sudden drops from this pattern likely indicated non-free-flow sections. Using this methodology, all non-free-flow sections were identified and removed for further analyses.

The geometry of the road sections used in the research was recreated using an algorithm based on the heading direction (Camacho-Torregrosa et al., 2015). Additionally, road sections were divided into 29 homogeneous road segments according to their Curvature Change Rate (*CCR*). This division can be performed by depicting the cumulative absolute deflection angle versus the road chainage. Hence, homogeneous road segments can be distinguished according to similar *CCR* behavior (FIGURE 3). *CCR* is defined as the sum of the absolute deflection angles (γ_i) divided by the length (L):

$$CCR = \frac{\sum |\gamma_i|}{L} \; (gon/km)$$

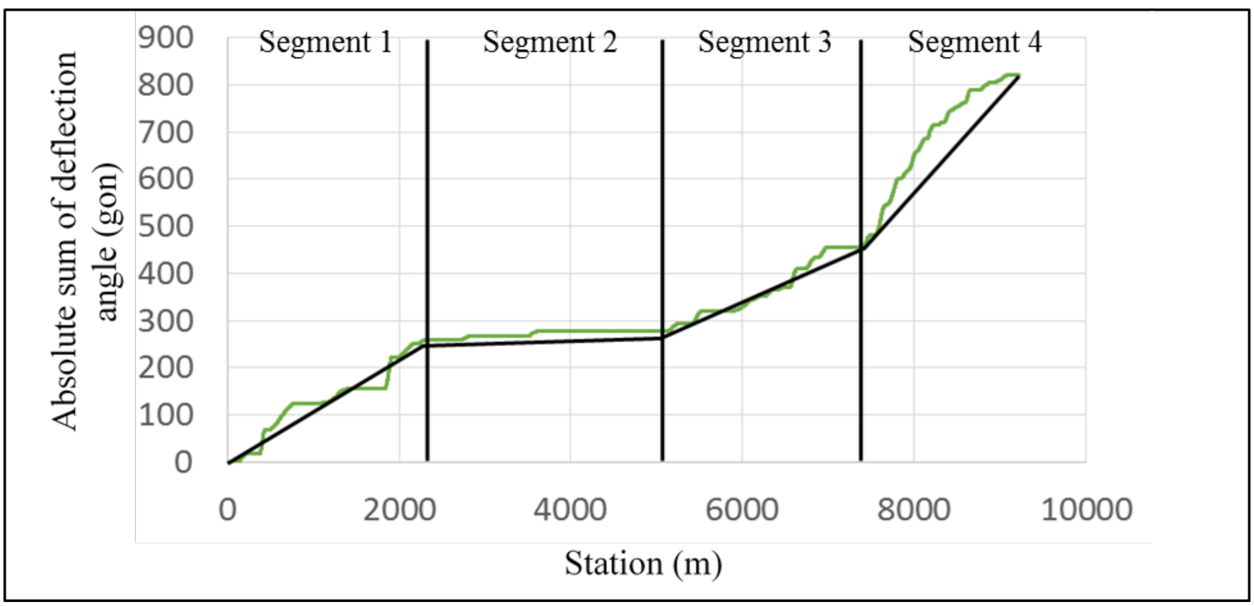

FIGURE 3 Determination of the homogeneous road segments.

Every road segment was characterized by geometric and operational features (FIGURE 4): L - length (m), CCR (gon/km), AR - Average radius (m), $Rmax$ - maximum radius (m), $Rmin$ - minimum radius (m), $\overline{V_m}$ - mean of the average speed profile (km/h), $\overline{V_{85}}$ - mean of the 85th percentile speed profile (km/h), $\overline{V_{50}}$ – mean of the 50th percentile speed profile (km/h), σ_{Vm} - deviation of the average speed profile (km/h), σ_{V85} - deviation of the 85th percentile speed profile (km/h), σ_{V50} - deviation of the 50th percentile speed profile (km/h), *g(+)* – average positive grade (%), *g(-)* – average negative grade (%), and *d* – drivers per direction.

Table 1 summarizes the main characteristics of the homogeneous road segments considered in this research.

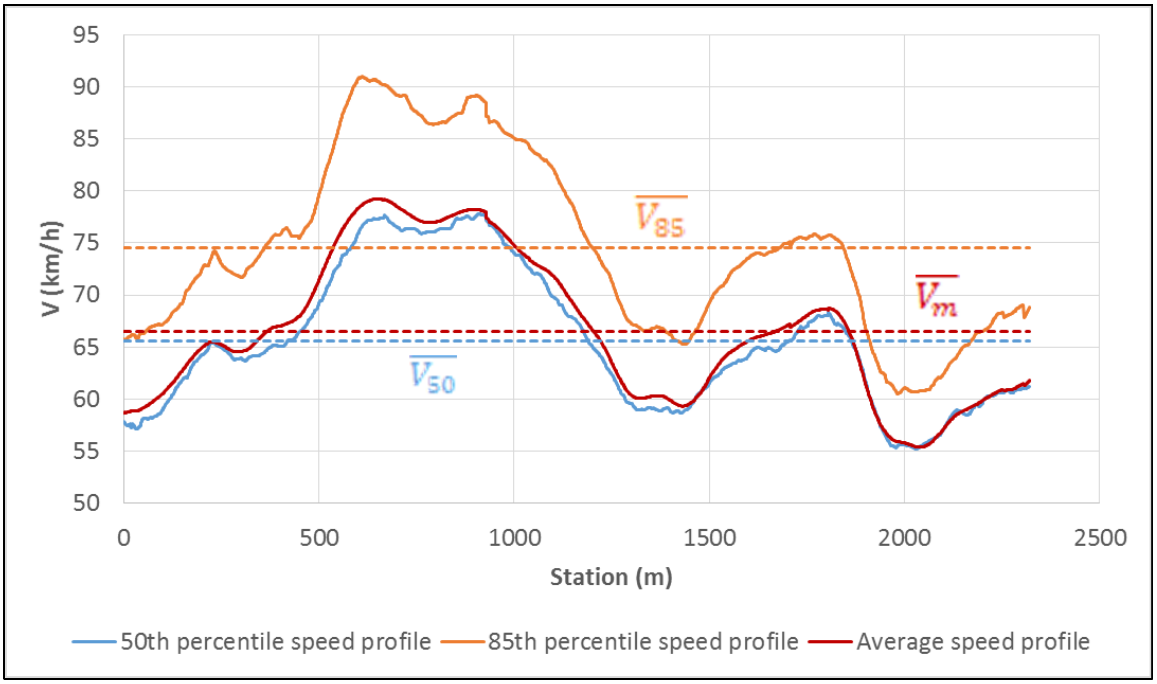

FIGURE 4 Operational variables.

3.3 Microscopic emission model

The microscopic model used to estimate CO_2 emissions was VT-Micro (Ahn et al., 2002), which predicts emission rates for individual vehicles using second-by-second vehicle speed (km/h) and acceleration (km/h/s) as input variables (FIGURE 5). Therefore, every individual meter-by-meter speed profile was converted into second-by-second speed and acceleration profiles. A smoothing algorithm was previously applied to ensure a feasible acceleration profile.

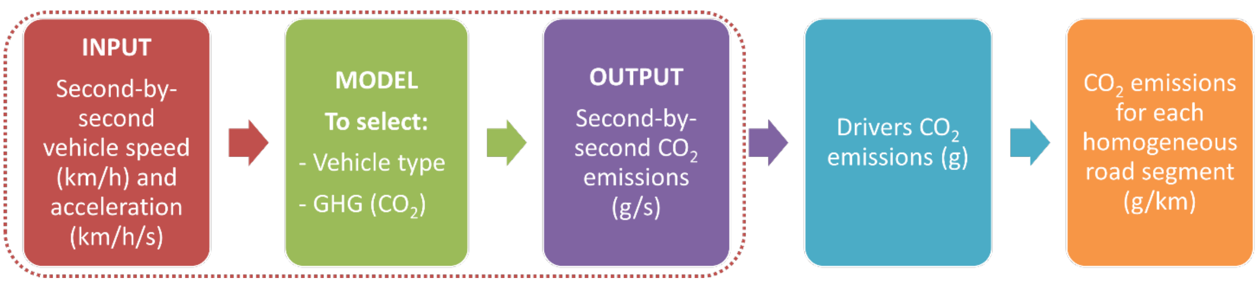

FIGURE 5 VT-Micro model procedure.

As mentioned previously, the model classifies the vehicles into different categories according to their emission characteristics (Rakha et al., 2004): six categories for light duty vehicles (LDV1, LDV2, LDV3, LDV4, LDV5, and LDV high emitters) and three categories for light duty trucks (LDT1, LDT2, and LDT high emitters). The observed vehicles were largely sedan-type vehicles and van-type vehicles. According to the classification required by the microsimulation model, there was a preponderance of light duty vehicles LDV3, LDV4, and LDV5. The simulation was only implemented for these vehicle types.

As a result of the microsimulation, the second-by-second CO_2 emission was obtained for every vehicle of each homogeneous road segment. Driver CO_2 emissions were determined as the sum of the CO_2 emissions along each homogeneous road segment. Finally, CO_2 emissions per length were determined for each homogeneous road segment as the average of all drivers CO_2 emissions divided by the length of the road segment, considering both directions (TABLE 2).

TABLE 2 Emission Rates at each Homogeneous Road Segment

ID	Forwards			Backwards			Road segment		
	CO_2 (g/km)			CO_2 (g/km)			CO_2 (g/km)		
	LDV3	LDV4	LDV5	LDV3	LDV4	LDV5	LDV3	LDV4	LDV5
1.1	143.06	134.63	168.64	132.92	123.47	155.09	137.99	129.05	161.86
1.2	146.58	135.61	176.20	149.13	138.19	177.94	147.85	136.90	177.07
1.3	175.17	158.72	217.76	173.49	156.51	214.31	174.33	157.62	216.03
1.4	159.28	146.52	191.86	148.51	137.31	178.08	153.90	141.91	184.97
1.5	131.73	122.56	152.35	143.73	135.08	164.70	137.73	128.82	158.53
2.1	152.64	140.30	186.63	147.68	135.64	180.49	150.16	137.97	183.56
2.2	153.22	142.20	184.06	143.63	133.47	172.58	148.42	137.84	178.32
3.1	142.95	132.10	173.03	165.34	151.45	200.08	154.14	141.77	186.56
3.2	145.50	135.47	171.88	140.73	130.58	166.77	143.11	133.02	169.33
3.3	146.46	135.19	175.68	160.15	147.58	193.05	153.30	141.39	184.36
4.1	151.42	142.32	178.08	127.85	120.44	147.80	139.64	131.38	162.94
4.2	129.79	121.59	153.03	157.88	147.29	185.84	143.83	134.44	169.43
5.1	148.15	138.74	174.79	133.98	126.35	156.90	141.07	132.54	165.84
5.2	141.68	134.64	163.15	135.73	129.03	156.59	138.70	131.84	159.87
5.3	128.92	121.07	150.60	156.08	146.36	184.63	142.50	133.72	167.61
6.1	169.78	155.92	205.82	141.96	130.74	172.36	155.87	143.33	189.09
6.2	129.82	120.64	154.84	162.72	150.43	195.19	146.27	135.53	175.02
7.1	144.96	134.59	174.51	144.02	133.62	173.52	144.49	134.11	174.02
7.2	146.38	136.50	174.88	143.21	133.07	172.69	144.79	134.78	173.79
8.1	144.54	134.58	171.44	133.00	123.72	156.91	138.77	129.15	164.17
8.2	137.79	128.26	164.26	145.38	135.72	173.31	141.58	131.99	168.79
9.1	171.94	158.54	206.97	132.74	123.31	160.50	152.34	140.92	183.74
9.2	135.68	125.78	163.73	160.95	148.57	194.70	148.32	137.17	179.21
9.3	143.34	133.26	171.10	144.95	135.28	172.87	144.14	134.27	171.99
9.4	148.22	136.50	180.70	146.84	135.39	179.17	147.53	135.95	179.93
10.1	148.70	139.47	175.26	140.06	131.81	164.26	144.38	135.64	169.76
10.2	147.65	136.04	179.21	163.74	150.70	198.37	155.70	143.37	188.79
10.3	147.97	137.20	178.09	147.49	136.91	177.35	147.73	137.05	177.72
11.1	133.64	124.65	159.98	147.88	136.99	178.18	140.76	130.82	169.08

4. ANALYSIS

This section describes the relationship between emissions previously obtained and geometric and operational variables.

4.1 Geometric Analysis

Different geometric variables were considered in the analysis (*AR*, R_{max}/R_{min}, *CCR*, and longitudinal grade). As expected, the effect of the longitudinal grade lacked statistical significance, since the road segments under study were flat to exclusively study the effects of horizontal alignment. Likewise, *AR* and R_{max}/R_{min} presented a high dispersion and the models associated with them showed low correlations (<0.30). Therefore, the study was focused on *CCR*, since this geometric variable did present a clear and close relationship with CO_2 emissions. According to the *CCR* definition, a low *CCR* value indicates that the road segment is mainly constituted by tangents and flat curves, whereas a high *CCR* value means that the road segment is mainly composed of sharp curves and short tangents.

FIGURE 6 shows that higher *CCR* values tend to produce higher CO_2 emissions. This result could be counterintuitive at first. High *CCR* road segments induce lower speeds, but the high number of speed variations (i.e., accelerations and decelerations) induce higher emissions. In addition, emissions are determined on a time basis, so the longer time needed to cover these road segments plays a major role as well.

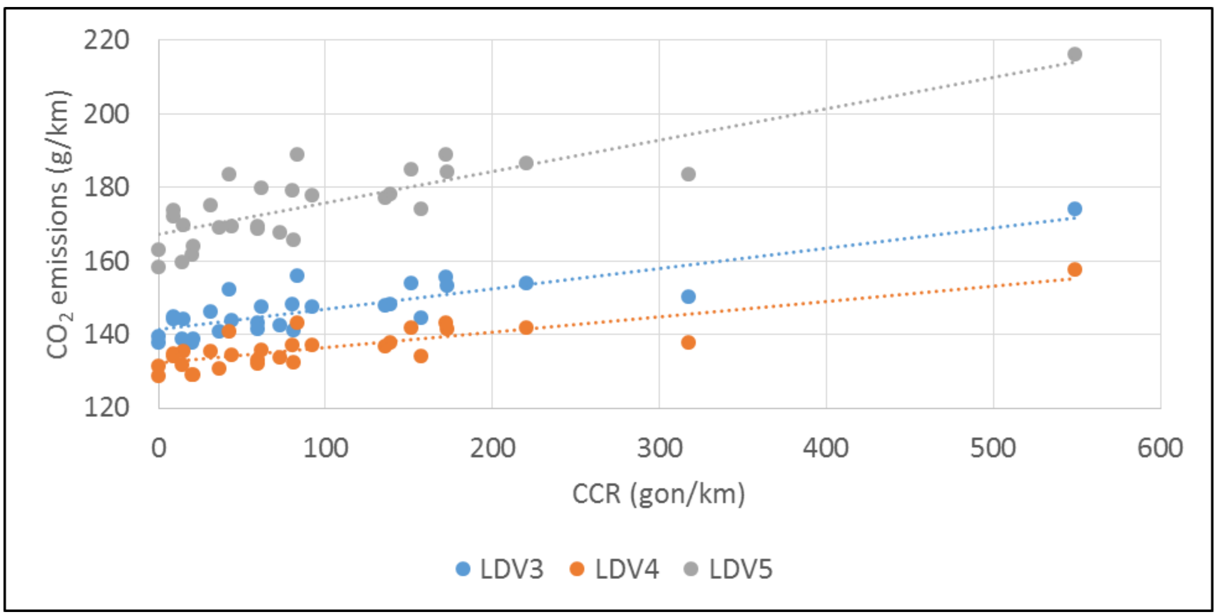

FIGURE 6 CO_2 emission rate vs. *CCR*.

To estimate the CO_2 emission rate from horizontal alignment design, several regression models with different functional forms were developed for the different types of vehicles. The models with the best correlations are shown in TABLE 3.

TABLE 3 Geometric models

Vehicle type	Model	R^2
LDV3	$E_{CO_2} = 141.45 + 0.0553 \cdot CCR$	0.6962
LDV4	$E_{CO_2} = 132.25 + 0.0419 \cdot CCR$	0.6673
LDV5	$E_{CO_2} = 167.19 + 0.0854 \cdot CCR$	0.6980
Where E_{CO_2} is CO_2 emission rate (g/km); and CCR is the Curvature Change Rate (gon/km).		

4.2 Operational Analysis

The same process was carried out to analyze the previously described operational variables. The relationship between CO_2 emissions and the different mean speeds ($\overline{V_m}$, $\overline{V_{85}}$, and $\overline{V_{50}}$) were similar. However, the mean of the average speed profile ($\overline{V_m}$) showed the best fit. In addition, the different types of vehicle described the same trend. CO_2 emission rate is higher for low speeds and decreases when speeds increase (FIGURE 7).

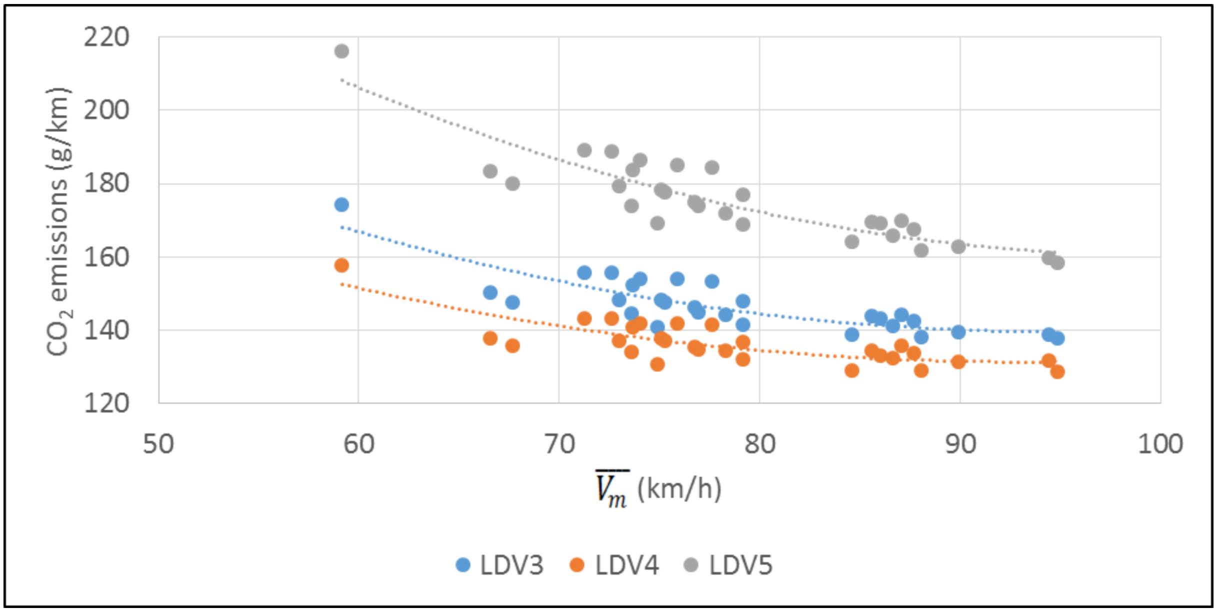

FIGURE 7 CO_2 emission rate vs. $\overline{V_m}$.

The same behavior was observed for the deviation of the average speed profile (σ_{Vm}) and the deviations of the different speed percentiles (σ_{V50} and σ_{V85}). However, the deviation of the average speed profile also presented the best correlation with CO_2 emissions. The lower the speed dispersion, the lower the CO_2 emission rate (FIGURE 8).

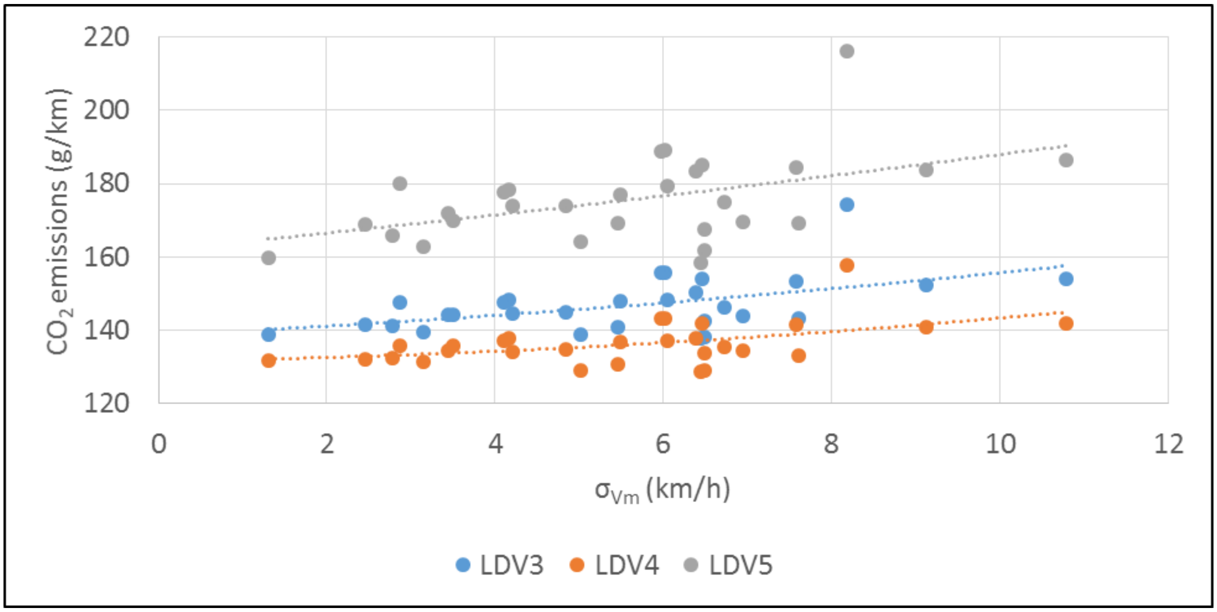

FIGURE 8 CO_2 emission rate vs. σ_{Vm}.

A single variable model was unable to accurately estimate emissions. Thus, models that combine both mean speed and speed dispersion were proposed (TABLE 4). These models were able to reflect how road segments with the same mean speed can have different CO_2 emissions due to different speed dispersions. This phenomenon can be observed in FIGURE 9 for the vehicle type LDV3, which presents a similar trend to the other vehicle types considered. Therefore, the higher the mean speed and the lower the speed dispersion, the lower the CO_2 emission rate.

TABLE 4 Operational models

Vehicle type	Model	R^2
LDV3	$E_{CO_2} = 124.95 + \dfrac{1}{e^{0.00183036 \cdot \overline{V_m}} - 1.08952} + 0.97094 \cdot \sigma_{V_m}$	0.7982
LDV4	$E_{CO_2} = 122.21 + \dfrac{1}{e^{0.00302829 \cdot \overline{V_m}} - 1.16165} + 0.69302 \cdot \sigma_{V_m}$	0.7318
LDV5	$E_{CO_2} = 128.11 + \dfrac{1}{e^{0.00061732 \cdot \overline{V_m}} - 1.02388} + 1.28842 \cdot \sigma_{V_m}$	0.8636

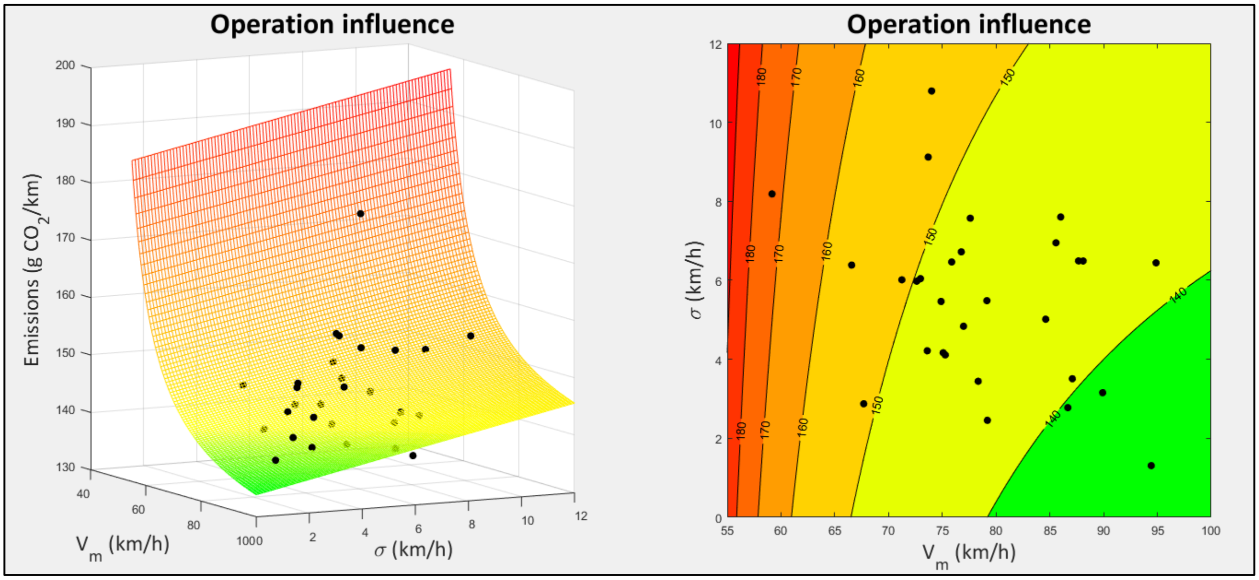

FIGURE 9 Operational model.

4.3 Combined Analysis

Geometric and operational variables have been shown to be highly related to CO_2 emissions and therefore to fuel consumption. Consequently, it is valuable to develop a set of expressions that use both kind of variables to better estimate the outcomes. Thus, different regression models were developed for each vehicle type considering *CCR*, the mean speed and speed dispersion as explanatory variables (TABLE 5). FIGURE 10 shows the model considering different speed dispersion values for the vehicle type LDV3. In this figure, the size of each point represents the speed dispersion and it can be observed how CO_2 emissions increase as speed dispersion and *CCR* increase and the mean speed decreases.

TABLE 5 Geometric and Operational Models

Vehicle type	Model	R^2
LDV3	$E_{CO_2} = 123.88 + 0.02122 \cdot CCR + \frac{1}{e^{0.00139126 \cdot \overline{V_m}} - 1.05337} + 0.75674 \cdot \sigma_{V_m}$	0.8198
LDV4	$E_{CO_2} = 122.67 + 0.01772 \cdot CCR + \frac{1}{e^{0.00280347 \cdot \overline{V_m}} - 1.12973} + 0.51696 \cdot \sigma_{V_m}$	0.7574
LDV5	$E_{CO_2} = 109.44 + 0.03030 \cdot CCR + \frac{1}{e^{0.00024591 \cdot \overline{V_m}} - 1.00204} + 0.95779 \cdot \sigma_{V_m}$	0.8827

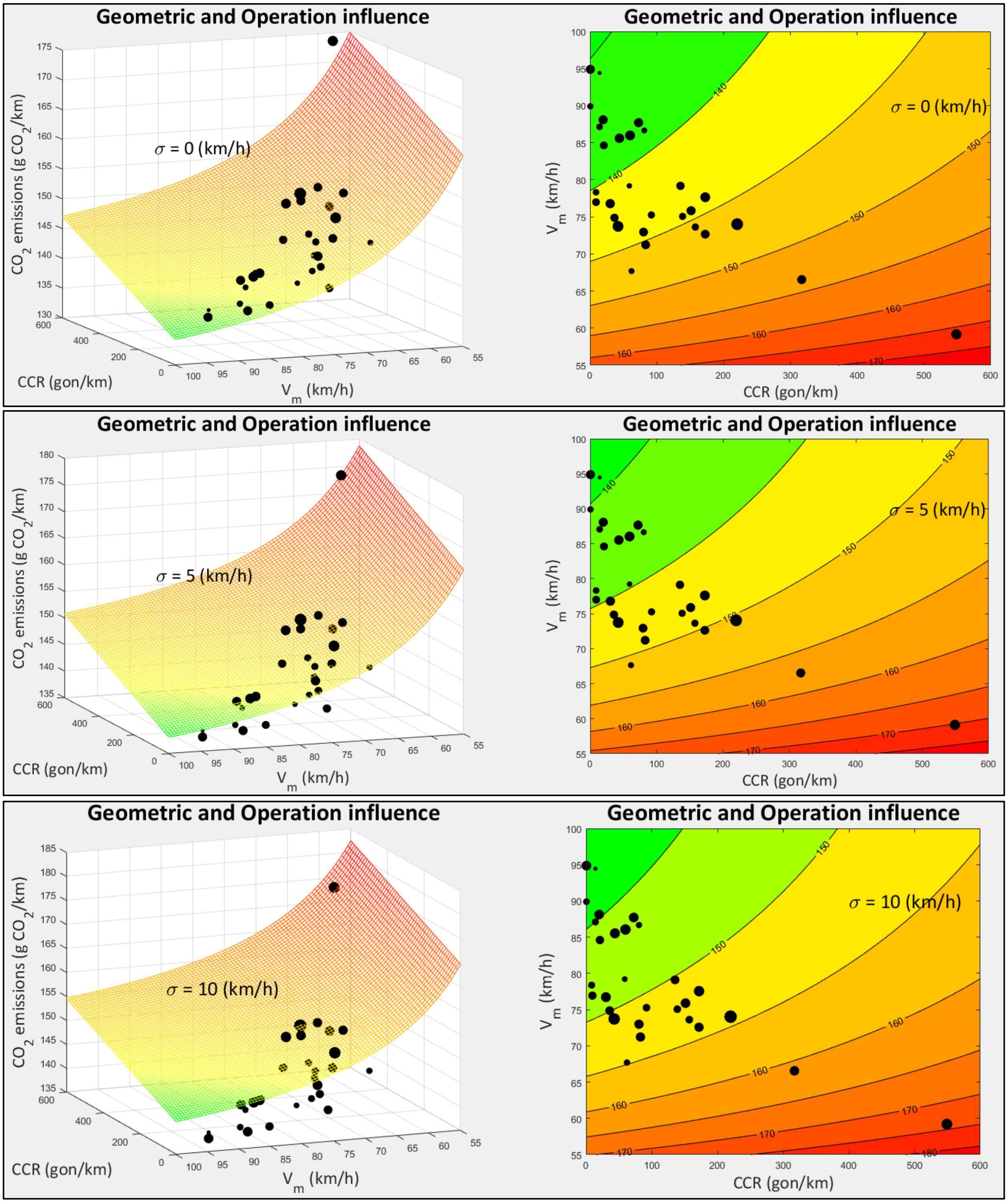

FIGURE 10 Geometric and operational model.

Finally, it must be noted that FIGURE 10 verifies the main hypothesis of the study, i.e., drivers tend to have lower speeds and higher speed dispersions when they drive along a road segment with a high *CCR*, and therefore produce high CO_2 emission volumes.

5. DISCUSSION

Year after year, people grow more concerned about environment, which is also being considered in the road geometric design process. However, there are few standards to guide the engineer to design environmentally friendly highways. Several studies have focused on this topic and several microsimulation models have been developed to estimate vehicle fuel consumption and emission rates during planning, design, and operation road stages (Rakha et al., 2004).

However, most of these studies use the average speed as explanatory variable. El-Shawarby et al. (2005) demonstrated that vehicle fuel consumption rates per distance are optimum between 60 and 90 km/h. Nevertheless, the results of this study have concluded that CO_2 emission rates decrease when the mean of the average speed profile increases, even for speeds higher than 90 km/h. This is due to vehicles spending less time covering the same distance, and the speed changes are lower, and so are the emissions. This relationship is not linear since the emission rate tends to be constant for higher speeds depending on the speed dispersion.

The main drawback of previous studies is the data on which they are based. Second-by-second speed and acceleration data are needed to estimate fuel consumption and emission rates. Some studies used data from a traffic microsimulation model with different scenarios and other studies from operating speed models and vehicle dynamic models.

The study outlined in this paper is based on actual driver continuous speed profiles collected in a naturalistic fashion, which better reflect the impact of the road geometric design on fuel consumption and emissions. In addition, some studies analyzed this impact considering emissions per trip (Ko, 2015; Ko et al., 2013 and 2012), instead of emissions per unit length. Despite this, these results showed the same trend as the present study results: sharper horizontal alignment produces higher level of emissions, whereas a smooth road designs allow drivers to reach higher speeds and reduce accelerations and decelerations, generating lower emissions.

Finally, different regression models have been developed considering geometric and/or operational variables for several vehicle types: LDV3, LDV4, and LDV5. The main aim of these models is to estimate the CO_2 emissions from the Curvature Change Rate of the homogeneous road segment (*CCR*), the mean of the average speed profile ($\overline{V_m}$), and the deviation of the average speed profile (σ_{Vm}). In addition, different models were developed according to the vehicle type to extend their application. The calibration of models for different vehicle types allows the determination of the overall contribution, if the traffic composition is known.

The model based on *CCR* is recommended for estimating CO_2 emissions at the design stage, when the speed profile is unknown. A better estimation can be performed for existing roads with the model based on *CCR*, $\overline{V_m}$, and σ_{Vm}. These models verify the hypotheses of the study: 1) the CO_2 emissions are highly influenced by the mean speed and the speed dispersion, and 2) the lower the mean speed and the higher the speed variation, the higher the emission rates. In fact, road designs with a high *CCR* value normally favors this situation, what causes higher CO_2 emissions.

Further research is needed to analyze the impact of the different geometric features of a road on vehicle fuel consumption and several emission rates. This research will be focused on the same actual individual continuous speed data as the present study.

6. CONCLUSIONS

CO_2 emissions are one of the main negative externalities caused by transport along with air pollution, congestion, noise, and crashes. In addition, vehicles are by far the main emitter of Greenhouse Gases (GHG) from transport. Most policy measures to address this problem focus on vehicles and fuel instead of road design. However, the key factors on fuel consumption and emissions are speeds and accelerations, which are highly related to the highway geometric design. This is why the main objective of this study was to analyze the impact of its characteristics on GHG, specifically CO_2 emissions.

To obtain CO_2 emissions, second-by-second speed and acceleration profiles were determined from a naturalistic data collection on 29 homogeneous two-lane rural road segments. These data were the input for the application of the microscopic emission estimation model VT-Micro. This model estimates vehicle emissions for hot stabilized conditions and does not consider the vehicle start effect. Every road segment was characterized by several geometric and operational features whose relationship with CO_2 emission rates were analyzed considering different vehicle types: LDV3, LDV4, and LDV5.

The results show that CO_2 emission rates increase when Curvature Change Rate (CCR) increases. Low CCR values indicate that the road segment is mainly constituted by tangents and flat curves, thus allowing drivers to perform at higher speeds without heavy accelerations. On the other hand, a road design with high CCR value produces a geometric control over the driver and, consequently, lower speeds with greater accelerations. A relationship between the mean of the average speed profile and the deviation of the average speed profile with CO_2 emissions was also found. CO_2 emission rate is higher for lower speeds and for higher speed dispersion.

Several regression models were developed to predict CO_2 emission rates on a specific homogeneous road segment for each vehicle type. These models present the Curvature Change Rate of the homogeneous road segment (CCR), the mean of the average speed profile ($\overline{V_m}$), and the deviation of the average speed profile (σ_{Vm}) as explanatory variables, because all of these variables showed an important influence on CO_2 emissions. These models can be used during the road design and operational stage.

As vehicle fuel consumption is strongly related to tailpipe CO_2 emissions, the findings presented are also applicable to vehicle fuel consumption. These conclusions may be the first step towards developing improved guidelines for designing environmentally sustainable highways, reducing fuel consumption, and emissions production.

Furthermore, these conclusions may be implemented for advanced navigation systems, as some allow route choice based on minimizing fuel consumption as well as GHG and pollutant emissions. Navigation systems could estimate emissions as a function of road geometric design instead of or complementing other variables such as traffic volume, density, and average speed.

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