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DEVELOPMENT AND VALIDATION OF A CONSUMPTION AND EMISSIONS PREDICTION METHODOLOGY FOR LIGHT VEHICLES BASED ON THE CLUSTERING OF INSTANTANEOUS AND RESIDUAL VEHICULAR POWER

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ABSTRACT

The speed with which the vehicle fleet is increasing gives the transport sector responsibility for 30% of the emissions generated by all sectors such as the industrial, food, etc., for this reason it is of great interest to quantify the impact of vehicles for assess in a better way the actions to be undertaken in order to mitigate the damage generated.

This study seeks to propose a new method for predicting fuel consumption and emissions of Carbon Monoxide, Hydrocarbons and Nitrogen Oxides generated by a vehicle under normal working conditions. Method a uses the value of the instantaneous vehicle specific power and the calculation of the average of the accumulated power of the last few seconds.

In this study, data was collected from forty vehicles working in an altimetry range between 0 and 4,000 m. a. s. l. , covering the coastal and inter-Andean region of Ecuador, adding 2,000 hours of measurement over a period of two years. This study makes it possible to establish a baseline of light automobile consumption in the described region and propose a method to prepare the region's emissions inventory.

Although in previous studies the method of vehicle specific power, PSV, has been used to characterize the areas of engine operation with a very acceptable precision, the method proposed in this study allows the margin of error to be reduced by up to 10% for cases when the car works in conditions of higher altitude.

To calculate the specific power, it is necessary to consider the forces that interact in the car's dynamics such as: aerodynamic force, rolling force, force generated by the weight and the internal force coming from the acceleration of the car, the sum of these forces allows to determine the

traction force that when multiplied by the speed gives us the instantaneous traction force, in addition to this value based on a Pearson correlation analysis it was determined that the accumulated specific power of the last seconds provides a greater range of precision to predictive calculus.

Keyboards: consumption and emissions, prediction methodology, flight vehicles, clustering

Introduction

In several Latin American countries, a much wider presence of light gasoline vehicles is marked , so this study focuses on obtaining a method that manages to predict with a high margin of precision certain operating parameters from the use of the specific vehicular power, which is A representative variable of engine load that over many years has been proven to have a high correlation with the emissions generated.

To obtain the data, a portable emissions monitoring system has been used to collect the speed profile and coordinates of the car to make a calculation base at a frequency of 1 Hz. As a result of this study, it was determined that the operating conditions are sensitive to the indicator obtained. This study estimates the rate of emissions generated by light vehicles using the VSP parameter. [1][2]

Once the calculation methodology has been proposed, a representative driving cycle is proposed to estimate the impact generated by a car under these operating conditions, however the cycle to be used can be any that is entered into the calculation platform.

The emissions analyzer that collects data at a microscale level allows the characterization of the variability of the operating parameters under different operating conditions, the same ones that can be faced with driving cycles that represent real traffic conditions representative of the real world. The study has shown that emissions are episodic in nature, i.e. strongly dependent on traffic conditions, with a A/B, there is a substantial increase with respect to a congestion level (D/E). [3]

A driving cycle is considered to be the profile of speeds facing time, which manages to capture in the most representative way possible the driving pattern in a given space, in such a way that it serves as a criterion for evaluating the behavior of cars for regulatory or research purposes. [4] A driving cycle includes many aspects of the type of circulation of the car and the road environment on which it operates, technology, type of driving, the functionality of the roads and the traffic light system are determining aspects that condition consumption and emissions generated. Factors such as aerodynamics and rolling resistance affect emissions since the sum of these drag forces itself are the demand of the driving cycle to the engine element of the car. These emission rates are presented in emission factors of grams per kilometer. Conceptual models have been developed by the Environmental Protection Agency of the United States (EPA) to approximate the calculation of emissions from road sources and the PSV parameter is a variable that manages to make a fairly accurate estimate of emissions. [5]. Certain driving cycles such as Beijing also uses the specific vehicular power as a construction mechanism, as can be seen in Figure 1 this characteristic parameter has been used as a basic criterion for selecting the most representative cycle.

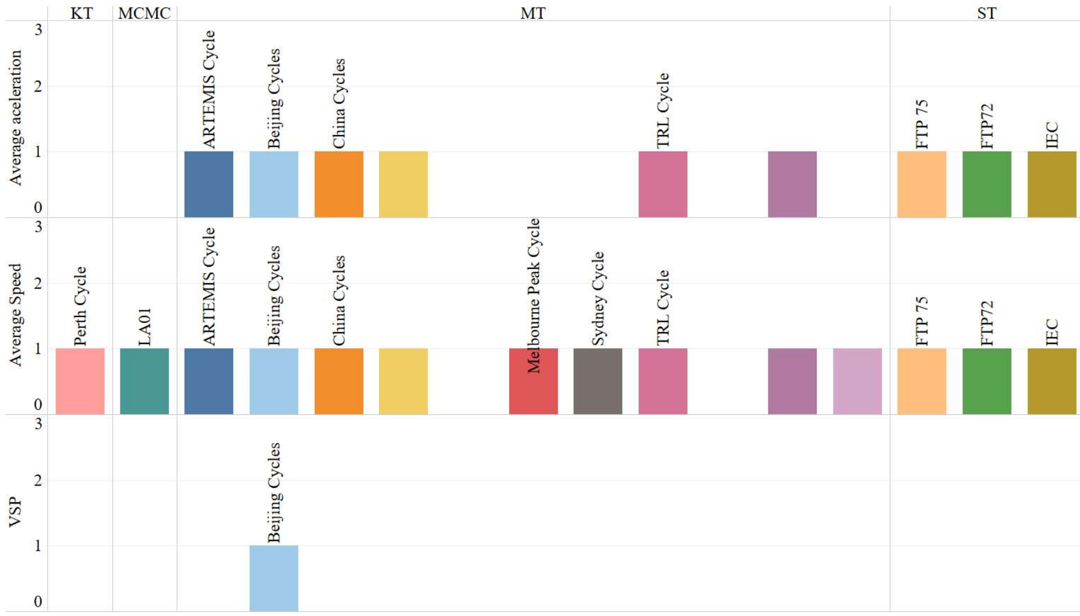

Figure 1. Characteristic parameters and construction methods of driving cycles, MT: Micro-trips, MCMC: Markov chain Monte Carlo, ST: select trip, KT: Knight tour, SAPD: speed-acceleration probability distribution, RMS: root

Different normative programs that group several driving cycles are shown in Figure 2 where it can be seen that on average they have 1000 seconds and 15 km of travel.

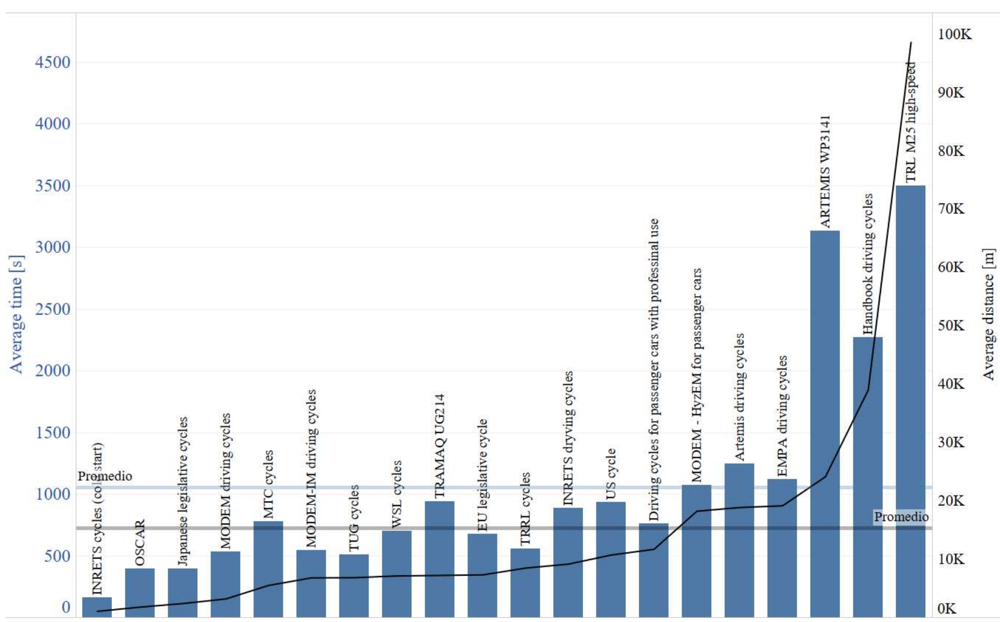

Figure 2. Average time and distances for different programs or groups of driving cycles

Drag forces such as downforce and rolling force are considered in the calculation of the PSV value, and the degree of road inclination has been shown to strongly affect the emission estimate. [6] This slope data was collected using a Satellite Positioning System, GPS, this method is reliable for the estimation of the slope with a verified level of error, using drawing techniques plotted in specialized software, less than 0.05%. In Figure 3 it is possible to observe the forces acting on the car. The degree of inclination of the road has an important effect on the generation, this impact has been studied by several authors, indicating that an incremento of 3.76% of the slope generates a factor of increase of 2 in emissions compared to a neutral slope. [7]. Previous studies show that hydrocarbons increase in the order of 0.04 g/mile for each 1% increase in slope while carbon monoxide increases 3 g/mile under the same increase in slope, when the vehicle increases its weight the emission values increase by 0.07 g/mile in hydrocarbons and 10.2 g/mile of CO in a slope of 4.5%. [8]

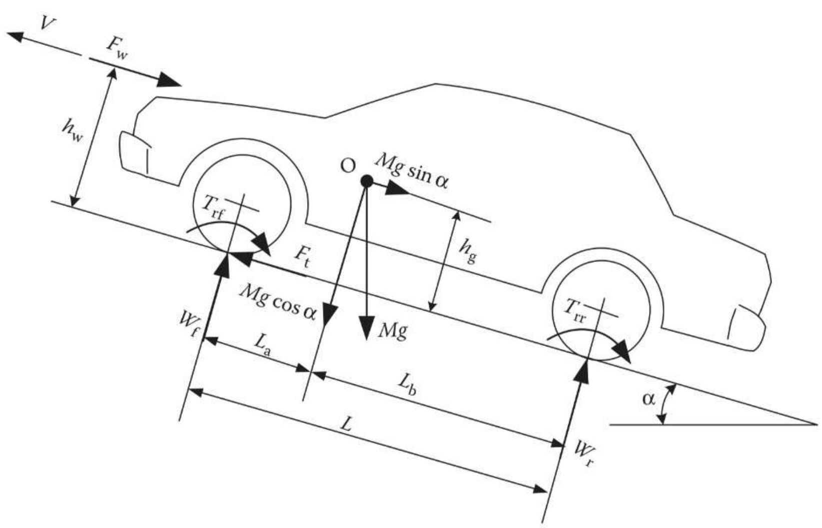

Figure 3, Forces interacting on a vehicle

The calculation of these forces is dimensioned as follows:

$$F_a = 0.5 * \rho * A * C_d * V_r^2$$ Equation 1

Where:

- $F_a \rightarrow$ Aerodynamic force
- $\rho \rightarrow densidad\ del\ aire$
- $A \rightarrow área\ frontal\ del\ vehículo$
- $C_d \rightarrow Coeficiente\ aerodinámico$

- $V_r \rightarrow$ $Resultante\ de\ la\ suma\ algebraica\ de\ la\ velocidad$
- $del\ automovil\ y\ la\ velocidad\ del\ viento$

$$R_x = f_r * M * g * \cos(\emptyset) \qquad \text{Equation 2}$$

Where:

- $R_x \rightarrow$ Gradient force
- $f_r \rightarrow Coeficiente\ de\ fricción\ del\ vehículo\ con\ la\ calzada$
- $M \rightarrow Masa\ total\ del\ automovil$
- $g \rightarrow Gravedad$
- $\emptyset \rightarrow Ángulo\ de\ pendiente\ de\ la\ vía$

$$W = M * g * sen(\emptyset) \qquad \text{Equation 3}$$

- W → Force generated by the weight of the car

$$F_T = F_a + R_x + W + M * a \qquad \text{Equation 4}$$

Dwhere:

- F_T → Tensile force
- a → Normalized acceleration of the car (mathematical model of 4th. Degree)

$$PSV_{inst} = \frac{F_T * V}{M} \qquad \text{Equation 5}$$

Where:

- PSV_{inst} → Instantaneous specific vehicular power
- V → Car speed

The value of specific vehicular power is calculated from the sum of the different drag forces: the aerodynamic force (Equation 1), the rolling force (Equation 1), the force generated by the weightEquation 2Equation 3). This value is added to the internal force of the vehicle (Equation

Equation 4 and the result is multiplied by the ratio of speed to mass of the car (Equation Equation 5

In Figure 4 you can see the interaction of the different forces that demand or deliver energy, the permanently positive aerodynamic force and increasing exponentially according to the speed at which the car rolls, in the case of the selected section it can be verified that due to the low speed its value is lower than the force of the weight which depends on the slope, being able to be negative when the car is descending, the force of inertia instead will depend on the acceleration, that is to say that it will take negative values when it is braking the car, finally the traction force is the algebraic sum of all the previous values and its positive sign will indicate the lapses in which the vehicle demands the impulse of the engine, while the negative sign will show the instants in the energy can be recovered. In the case of electric vehicles, it is these sections where the batteries can be charged by the wheel system.

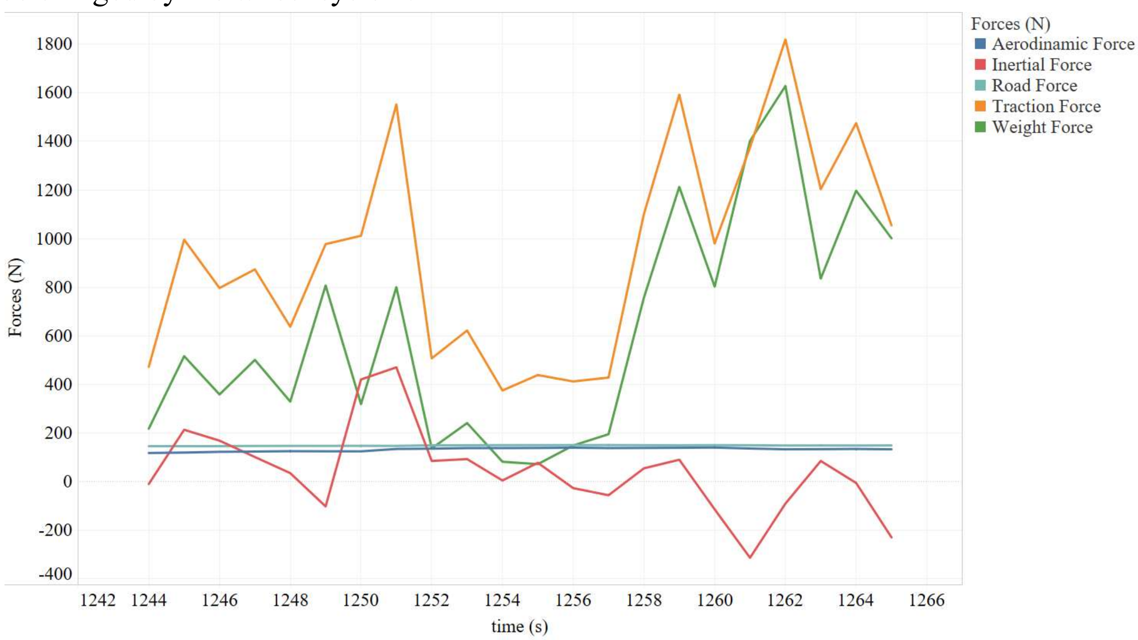

Figure 4. Forces interacting on the vehicle

The method shown manages to predict consumption and emissions, however, the specific vehicular power contemplated only includes a condition of temporary operation and for this reason lacks the observance of the aspects prior to those of operation and performance of the car. For this reason it is necessary to include a criterion that quantifies the demand and energy delivery in such a way that greater precision is given to the study. The statistical basis of this criterion was obtained by performing a correlation analysis between the current and previous PSV with a period considered between 15 and 3 seconds prior to the current working condition.

Table Table 1 conducts a comparative study between the criteria that, when considering a regression, generate the highest values of R^2, while in Table 2 an analysis of Pearson's correlation between consumption and the accumulated PSV criterion was performed, where a high link was found between consumption and the average PSV of the last 7 previous seconds. to the current state by providing a quantification of the precondition of the vehicle's operating status.

Table 1. Analysis of better predictors for fuel consumption determination

Whose	*R^2*	*R^2 (ajust.)*	*R^2.(before.)*	*Cp deMallows*	*PSV*		*2*	*3*	*4*	*5*	*6*	*7*	*8*	*9*	*10*	*11*	*12*	*13*	*14*	*15*
1	*23.0*	*23.0*	*22.7*	*77.3*	*0.60245*							*X*								
1	*21.4*	*21.4*	*21.0*	*108.9*	*0.60854*	*X*														
2	*26.6*	*26.5*	*26.0*	*6.6*	*0.58839*	*X*														*X*
2	*26.5*	*26.4*	*25.9*	*9.7*	*0.58901*	*X*													*X*	
3	*27.1*	*27.0*	*26.4*	*-1.7*	*0.58654*	*X*	*X*													*X*

Table 2.- Analysis of correlation between fuel consumption and previous PSV values

	Fuel flowrate/hour(gal/hr.)	PotenciaTotal (KW)	2	3	4	5	6	7
Total Power (KW)	0.462							
2	0.452	0.697						
3	0.454	0.692	0.962					
4	0.457	0.681	0.928	0.977				
5	0.457	0.663	0.898	0.952	0.984			
6	0.456	0.646	0.869	0.926	0.964	0.988		
7	0.479	0.720	0.862	0.913	0.949	0.972	0.987	
8	0.452	0.613	0.816	0.875	0.919	0.952	0.976	0.983
9	0.449	0.601	0.792	0.851	0.895	0.931	0.959	0.970
10	0.447	0.589	0.772	0.829	0.874	0.910	0.941	0.954

Methodology

Data collection

Speed, consumption, emissions were collected at a sampling rate of 1 Hz over a period of 2000 hours using 20 light vehicles of different categories in a range between 0 and 4000 meters above sea level. The operating parameters of the cars were obtained using an OBD monitor and a platform built by our team under Python programming language. The fuel measurement process was experimentally validated by comparing it with alternative methodologies such as gravimetric and fuel flow to the rail. In Table 3 it is possible to see the main parameters obtained from the cars, referring to the operation and the emissions produced.

Table 4 shows the specifications of the portable emissions analyzer used, which allowed collecting data on the volume generated by the exhaust of: Carbon Monoxide, Hydrocarbons, Nitrogen Oxides, Oxygen and Carbon Dioxide. This data collection will allow a temporal analysis of emissions with respect to the dynamics of the car.

Table 3. Parameters obtained from cars using the OBD II device and the emission analyzer

Emissions Analyzer Readings	*Chemical formula*	*Reading of car sensors by OBD II*	*Reference PID (hex)*
Carbon dioxide	CO_2	*Short- and long-term fuel adjustment*	*06 / 07 / 08 / 09*
Carbon monoxide	CO	*Car speed*	*0D*
Total, of hydrocarbons	THC	*Engine load*	*04*
Nitrogen dioxide	NO2	*Instant fuel consumption*	*5E*
Hydrogen monoxide	NO	*Throttle position*	*11*
Oxygen	O_2	*Motor speed*	*0C*
		Coolant temperature	*05*

Table 4. Emission Analyzer Specifications

Gas	*Symbol*	*Range*	*Units*	*Precision*	*Measuring method*
Carbon dioxide	*CO2*	*0 - 20*	*%*	*0.01*	*Infrared Spectrometry*
Carbon monoxide	*CO*	*0 - 15*	*%*	*0.01*	*Infrared Spectrometry*
Total Hydrocarbons	*THC*	*0 - 10K*	*ppm*	*0.01*	*Infrared Spectrometry*
Nitrogen oxide	*NOx*	*0 - 5K*	*ppm*	*20*	*Electrochemical detection*
Oxygen	*O2*	*0 - 25*	*%*	*0.01*	*Electrochemical detection*
Lambda	λ	*0.5 - 10*	*-*	*0.01*	*Calculated*

The characteristics of the cars are shown in Table 5 where you can see the type, emission standard, displacement, compression ratios, etc. The selection of these vehicles was considering the brands and models that exist in greater quantity within each automobile segment, with the purpose of obtaining a representative sample of the automotive fleet of Ecuador, which is very similar in the different countries of Latin America. The set of vehicles was instrumented for two years in different operating conditions, with the same drivers seeking to give independence of results with respect to the operator, this allowed it to be possible to isolate the driver criterion to focus the study on the rest of the parameters, purpose of this study.

Table 5. Types of instrumented cars

Vehicle	*1*	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*9*	*10*
Guy	*Van*	*Since*	*Hatchback*	*Since*	*Since*	*Since*	*Since*	*Since*	*Suv*	*Truck*
Emissions standard	*EURO III*	*EURO IV*	*EURO V*	*EURO V*	*EURO IV*	*EURO IV*	*EURO IV*	*EURO IV*	*EURO V*	*EURO IV*
Displacement CC.	*1173*	*1399*	*1397*	*1397*	*1498*	*1498*	*1598*	*1799*	*1984*	*2237*
Compression ratio	*10:1*	*10:1*	*10.5:1*	*10.5:1*	*9.5:1*	*9.5:1*	*10.5:1*	*9.8:1*	*9.6:1*	*10:1*
Type of admission	*ON*	*ON*	*ON*	*ON*	*ON*	*ON*	*ON*	*ON*	*Turbocharged*	*ON*
Type of injection	*MPFI*	*MPI CVVT*	*MPI CVVT*	*MPI CVVT*	*MPFI*	*MPFI*	*MPI*	*MPI*	*TFSI*	*MPFI*
Maximum torque Nm-RPM	*106 @ 3500 - 4500*	*136 @ 5000*	*137 @ 5000*	*138 @ 5000*	*128 @ 3000*	*128 @ 3000*	*153 @ 3800*	*165 @ 4000*	*350 @ 1500 - 4500*	*190 @ 2.800*
Maximum power KW-PRM	*59 @ 6000*	*79 @ 6300*	*67 @ 6200*	*68 @ 6200*	*62 @ 5600*	*62 @ 5600*	*77 @ 5600*	*89,55 @ 5800*	*171.5 @ 4700 - 6200*	*79 @ 4600*
Empty weight Kg.	*1230*	*1133*	*1263*	*1074*	*1040*	*1040*	*5*	*1211*	*1830*	*1740*

The data acquisition equipment is a Raspberry Pi 3, which has a GPS module, bluetooth and network adapter. This data was uploaded to the cloud using a Huawei modem that works with 3G technology. The connection scheme is shown in Figure 5.

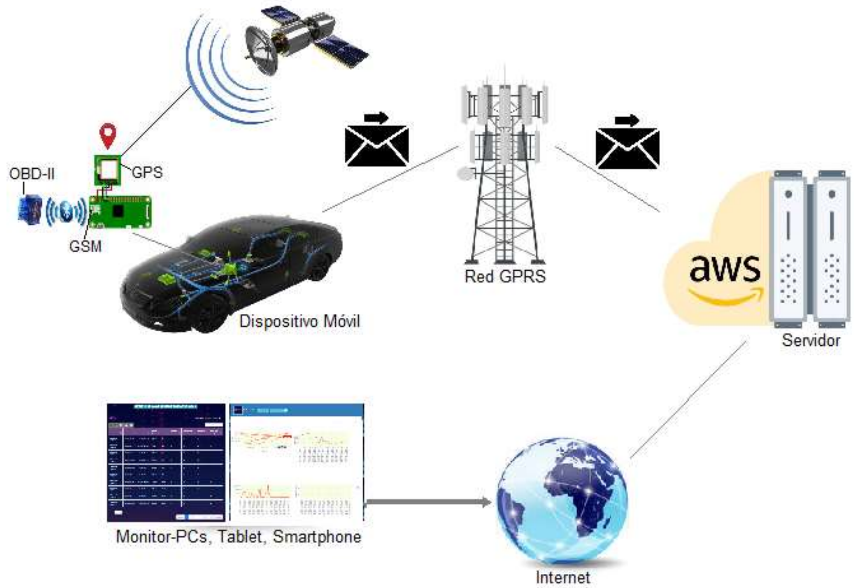

Figure 5. 3G network connection scheme for the acquisition of vehicle operating parameters

The data obtained are shown in Figure 6. Frequency distribution of speeds and accelerations where velocity and acceleration parameters were characterizedthroughout the analysis time. Accelerations close to 0 are the most repetitive and speeds between 56 and 63 km / h.

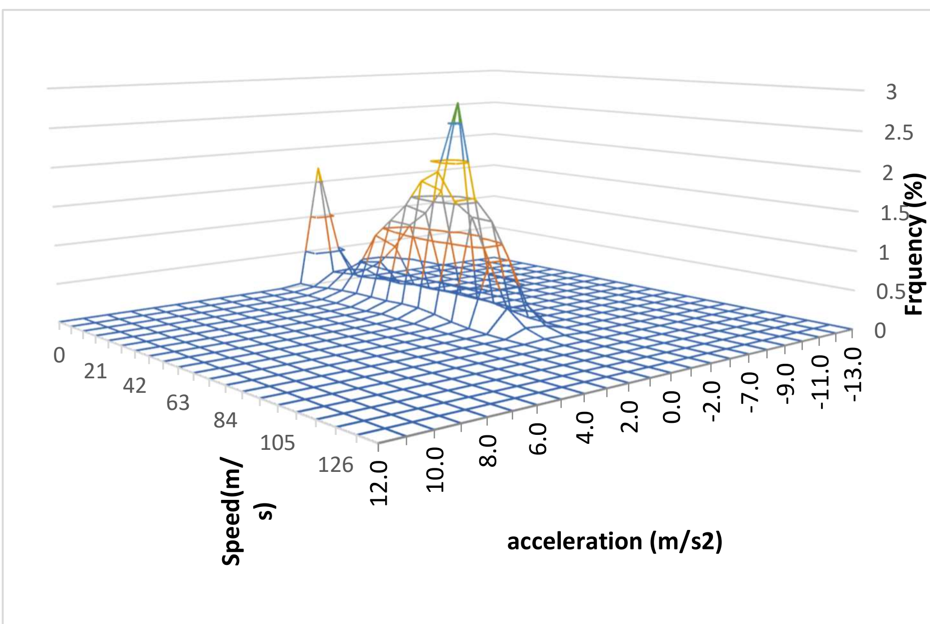

Figure 6. Frequency distribution of speeds and accelerations

Data filtering and analysis

The data obtained were filtered considering the particularities of the dynamics of the car, where accelerations out of range or slopes greater than 15% were analyzed to develop a protocol for disabling these data. Another criterion to take into account was the gap between the data obtained by the OBD II monitor and the emissions analyzer, in such a way that it is possible to perform an accurate analysis of events, this because the analyzer for its operation mechanics that requires a lapse of time with respect to the OBD II device, Table 6 shows an estimate of the lag times, which may vary with respect to theparticularities of each measurement. The lag between the two measurement instruments mentioned requires a synchronization process based on parameters in which they react with high correlations between the two equipment. The accelerator drive has an immediate response on the generation of hydrocarbons and the increase in CO2, this high existing correlation was used to determine the existing lag through a comparative statistical analysis between several deltas of time between 2 and 10 seconds for the selection of the highest Pearson correlation index.

Table 6. Recording of times required for the measurement of the analyzer and the OBD II monitor

OBDII		*WITH 6.3*	
Event	*Time[s]*	*Event*	*Time[s]*
Action of pressing the pedal	*1,5000*	*Action of pressing the pedal*	*1,5000*
OBD data logging	*0,0020*	*Action of the electronic butterfly*	*0,0010*
Data Capture App Torque	*1,0000*	*Injection time*	*0,0025*
Log on file	*0,5000*	*Burning time*	*0,0014*
		Gas escape time	*0,0005*
		Measurement time	*2,0000*
		Log on file	*2,3000*
Total	*3,0020*	*Total*	*5,8054*

Results

Among the resultsthat can be drawn from this study is the importance of defining the impact of altitude on fuel consumption and emissions. Using the criterion of Vehicle Specific Power it is possible to generate 13 study bins and thus achieve an approximation for each range of PSV.

The United States Environmental Protection Agency has presented the following formula for the calculation of PSVs considering certain approximations:

$$VSP = 0.278v\left[0.305a + 9.81sin\left(atan\left(\frac{r}{100}\right)\right) + 0.132\right] + 0.0000065 * v^3$$ Equation 6

A contribution of this study is to integrate a criterion of remaining power which includes an indicator related to the power of the last seconds, to determine the previous time to be considered, a correlation analysis was carried out with respect to different previous periods and a favorable peak of Pearson's correlation was found when the previous 7 seconds were analyzed.

In this way, these two criteria were considered to group the data with similar consumption conditions under the clustering method. Using the k-means clustering criterion, the elements are grouped into 6 clusters, the algorithm divides the data into k agglomerates, where each group has a centroid, which is the average value of all points, the mechanism is iterative that minimizes the distances between the individual points in a group, the variables of instantaneous power and accumulated previous power are used as a threshold to divide the data.

Starting with a group, the method chooses a variable whose mean is used as a threshold to split the data in two. The centroids of these two parts are then used to initialize k-means to optimize the membership of the two groups. Next, you choose one of the groups to divide and choose a variable within that group whose mean is used as a threshold to divide that group in two. K-means is then used to divide the data into groups, initialized with the centroids of the two parts of the divided group and the centroid of the remaining group. This process is repeated until a certain number of groups is reached.

Lloyd's algorithm with squared Euclidean distances is used to calculate the grouping of k-means for each k. Combined with the division procedure to determine the initial centers for each k > 1, the resulting grouping is deterministic and the result depends solely on the number of clusters. In it it is possible to appreciate the different clusters that will be used to generate the prediction model and environmental emissions. [9]

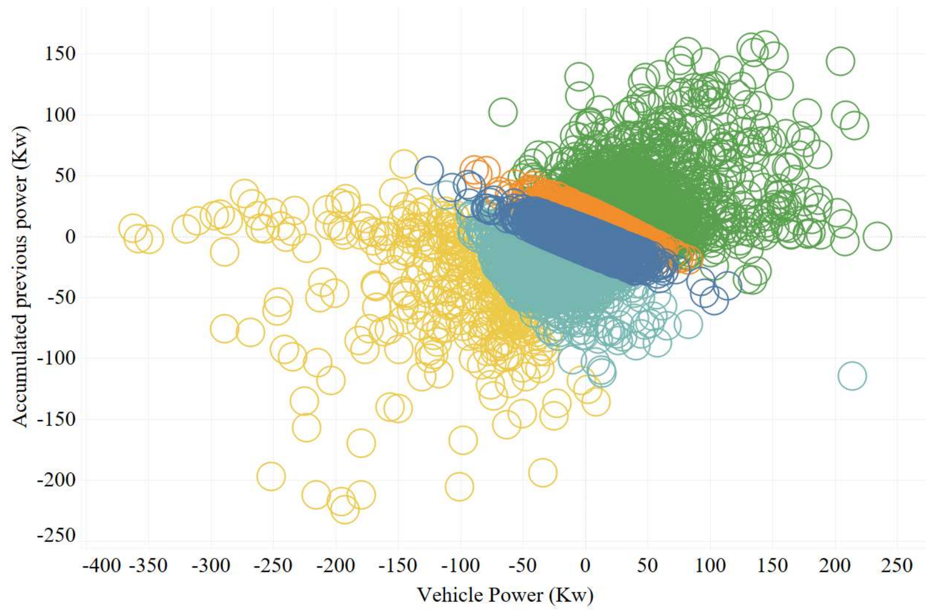

Figure 7. Clustering from instantaneous power and accumulated previous power

These sets of data generated from each of the five clusters are used to generate the consumption prediction model, as shown in Figure 7. Clustering from instantaneous power and accumulated previous power.

Table 7. Features of the clustering process

Number of clusters:	5
Number of points:	152979
Sum of squares between groups:	172.19
Sum of squares within groups:	86.694
Total sum of squares:	258.89

Table 8. Understanding clusters

Clusters	Number of items	Total Power Sum (Kw)	Sum of Remaining Power (Kw)
Cluster 1	57085	-0.96818	-1.0074
Cluster 2	55311	8.5657	8.9002
Cluster 3	16474	-16.495	-15.974
Cluster 4	23803	21.916	19.981
Cluster 5	306	-117.77	-47.328

In Figure 8. Box and whisker diagram for fuel consumption expressed in gal/hour with respect to 1000 m altimeter bins shows the effect of altitude on fuel consumption, the study sectioned the Bin corresponding to 0 Kw of power to the wheel to determine the effect of altitude maintaining the same power developed in such a way that the results are comparable.

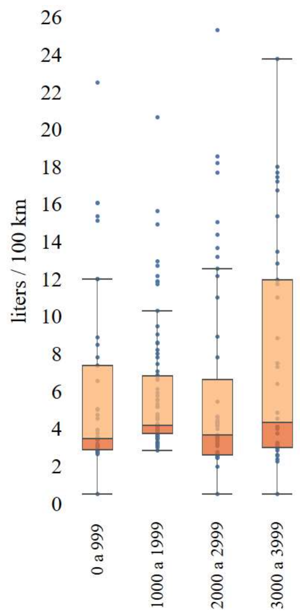

Figure 8. Box and whisker diagram for fuel consumption expressed in gal/hour with respect to 1000 m altimeter bins

Table 9. Analysis of variance of a factor an analysis of variance of the results obtained to conclude on whether the values of the averages of each group of consumption values are statistically different with a significance of 5%. Table 10 summarizes the confidence intervals over which the consumption values for the selected BIN are found.

Table 9. Analysis of variance of a factor

Fountain	GL	SC Ajustado	MC Ajustado	F-value	P value
Altitude(m)	3	105.5	35.16	1.52	0.211
Error	207	4790.0	23.14		
Total	210	4895.5			

Table 10. Consumption confidence intervals for each altitude BIN

Altitude(m)	*N*	*Media*	*Desv.Est.*	*95% CI*
0 a 999	*42*	*5.904*	*4.893*	*(4.441; 7.368)*
1000 a 1999	*80*	*5.893*	*3.425*	*(4.833; 6.954)*
2000 a 2999	*51*	*6.175*	*5.497*	*(4.847; 7.503)*
3000 a 3999	*38*	*7.795*	*6.086*	*(6.256; 9.333)*

Table 11 shows an anova comparative analysis to determine by Tukey's test whether the means of each altimetry group to discern whether the results are significantly different or not. This honestly meaningful difference test compares the means of the 4 blocks, the first between 0 and 999 masl, the second between 2000 and 2999 masl and so on until reaching 4999 masl. The null hypothesis proposes that all treatments are the same while the alternative hypothesis states that at least one of the means is different, in this case and according to the P value of Table 9 greater than0.05 it is determined that there is not enough evidence to deny the null hypothesis and it is accepted as true. It is necessary to consider that for this analysis Cluster 5 was considered.

Table 11. Tukey's comparative analysis to determine significant differences between means

Altitude(m)	N	Media	Grouping
3000 a 3999	38	7.795	A
2000 a 2999	51	6.175	A
0 a 999	42	5.904	A
1000 a 1999	80	5.893	A

In Figure 9 a comparative analysis of fuel consumption is made with respect to the angles of inclination of the road, it is possible to conclude that there is an increase in consumption of 0.93 (l / 100 km) for each degree in which the slope of the road increases. In the case of negative slopes they also turn out to be counterproductive when exceeding 4 degrees because there is an increase in consumption of 0.36 (l / 100km) for each degree in which the slope increases when descending, this effect is suggested to the recurrent use of the brake and the energy waste that emerges from this process.

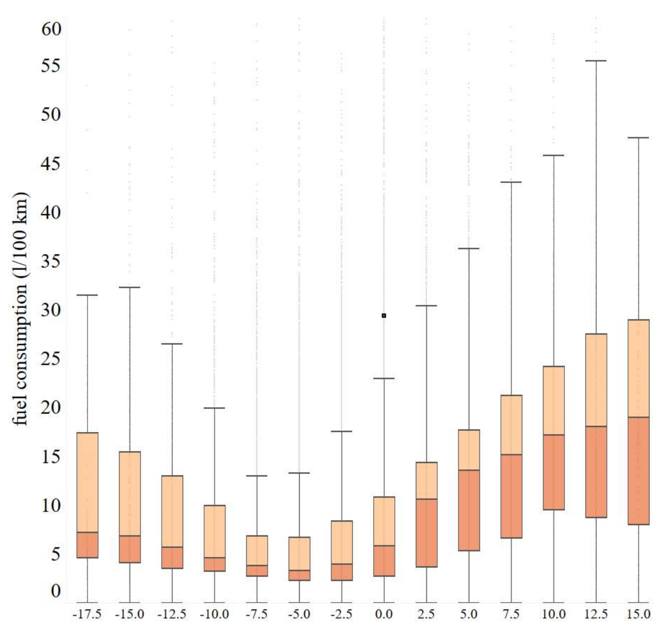

Figure 9. Fuel consumption evaluated on different slope bins between -17.5 and 15 degrees

Figure 10 graphically shows the median values for consumption and emission factors for the different clusters formed, while in Table 12Table 12 and hydrocarbons.

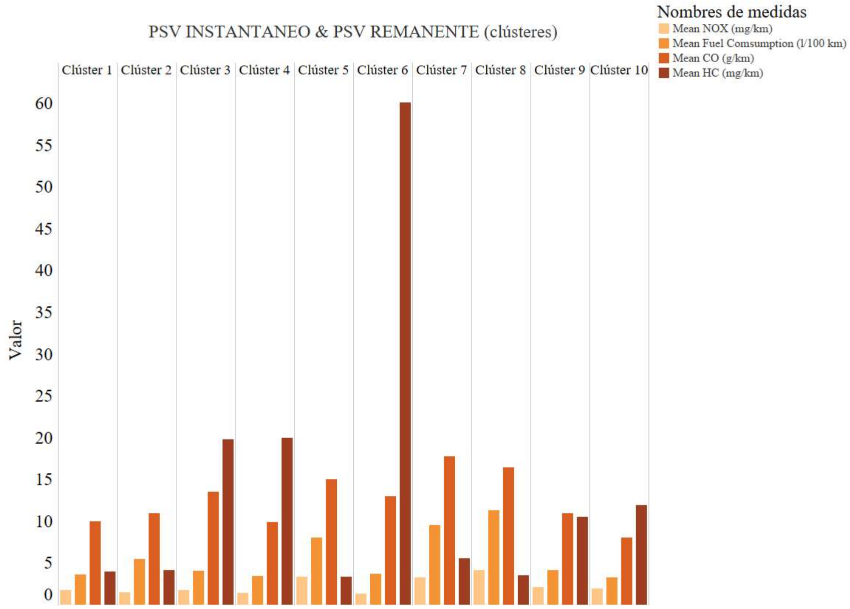

Figure 10. K-mean based clustering for instantaneous PSV vs remnant PSV for consumption prediction and emission factors

Table 12. Consumption and emission factors for the different clusters

	C1	C10	C2	C3	C4	C5	C6	C7	C8	C9
Mean CO (g/km)	10.0	8.1	11.0	13.5	9.9	15.0	13.0	17.7	16.5	10.9
Mean Fuel Comsumption (l/100 km)	3.6	3.3	5.5	4.1	3.4	8.1	3.7	9.5	11.3	4.1
Mean HC (mg/km)	4.0	11.9	4.2	19.8	20.0	3.4	60.1	5.6	3.5	10.5
Mean NOX (mg/km)	1.8	2.0	1.5	1.8	1.4	3.4	1.3	3.3	4.2	2.1

Conclusions

From the empirical data shown in this study has shown the sensitivity between the slope of the road and fuel consumption while the altitude at which it is circulating did not show a statistically significant result to conclude on a considerable effect on consumption in light vehicles.

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