Micro-analysis of a single vehicle driving volatility and impacts on emissions for intercity corridors

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Abstract

A deep understanding of driver behavior is an important step to improve road safety and environmental performance. Volatility can be defined as the extent of variations in driving, which can be characterized by accelerations/braking, lane change, and unusual high speed for roadways conditions. There is a lack of knowledge on what concerns the relationship between driver's volatility and exhaust emissions and how driving volatility can be used as safety eco-indicator. This article explores a driving volatility concept for assessing tailpipe emissions and driving behavior classification. For that purpose, an empirical approach that combined vehicle activity and emission rates for light duty vehicles was used. Field measurements were collected from four probe vehicles in one partly urban/rural, and two highway routes using Portable Emission Measurement Systems, Global Positioning System receivers, and On-board Diagnostic scan tool, to measure real-world tailpipe emissions, position and engine activity data. Acceleration-based parameters, including relative positive acceleration and mean of positive acceleration, acceleration, vehicular jerk, and power demand thresholds were used to detect differences in emissions for different driving styles. Results indicated that vehicular jerk impacted carbon dioxide and nitrogen oxides per unit distance regardless of driving style and route type, especially from negative to null jerk values and during positive accelerations. There is potential to incorporate the analyzed thresholds into a driver decision support algorithm by considering safety and environmental aspects through warning messages.

Keywords: Driving volatility; tailpipe emissions; vehicular jerk; power demand

1. Introduction and Research Objectives

Road transport has long-lasting negative impacts on road safety, human health, and wellbeing. In 2018, more than 25 000 people lost their lives on European Union (EU) roads, which represents just 4% of reduction over the last five years (ETSC, 2019). This number of fatalities is still far from EU target of 15 760 fatalities for 2020 (EC, 2019EC. (2019).

Road transportation represented more than 70% of the transport-related greenhouse gas emissions (EU, 2018), and it is a relevant contributor of air pollution as means of nitrogen oxides (NO_x) and particulate matter (PM) emissions (EEA, 2018; EEA, 2019). New generation of vehicles have emerged as a reaction to energy shortages and to meet restricted emission standards, so that a deep knowledge about its impacts on both exhaust emissions and safety by taking into account driving behavior aspects is a matter of importance. Understanding the instantaneous driving decisions, distinguishing normal from anomalous, to reduce both the probability of crashes and emission amounts in road trips has been

pointed out one of the critical issues in transport in the next 20 years (NAS, 2018).

Driving activity can be characterized by performance metrics or driving style/behavior (Rolim et al., 2016). Driving above the speed limit or above the recommended speed for a certain road situation is normally defined as an aggressive behavior (Fitzpatrick et al., 2017; Lee & Jang, 2019). Speed is a parameter that can be used to characterize driving behavior at the environmental level, that is, if the driver has an eco-driving behavior (Muslim et al., 2018), and it depends partly on the roadway conditions, including surrounding traffic, obstacles, pavement, and speed limits (Åberg et al., 1997; Haglund & Åberg, 2000). Faria et al. (2017) used some variables such as speed and acceleration to classify driving behavior as aggressive and non-aggressive at urban areas. Prior studies have provided several acceleration cut-off points as the thresholds for identifying aggressive driving behaviors (Kilinç & Baybura, 2012; Lárusdóttir & Ulfarsson, 2015; Choi & Kim, 2017; Deligianni et al., 2017). To assess variations in driving behaviors under different road contexts, varying acceleration thresholds, given different speeds for identifying anomalous driving were proposed (Liu et al., 2014; Lárusdóttir & Ulfarsson, 2015; Wang et al., 2015). Lane changing combined with vehicle speed or acceleration could also be used to identify aggressive driving behaviors (Yu et al., 2018). Traffic conditions (at congested or non-congested), traffic violations, the presence of police or traffic enforcement can also be used to classify safe or unsafe driving behaviors (Habtemichael & Santos, 2014; Harris et al., 2014; Stanojević et al., 2018; Zhang et al., 2019). Some authors stated that the Relative Positive Acceleration (RPA), the Mean of Positive Acceleration (MPA) and the 95th percentile of the product of vehicle speed and positive acceleration greater than 0.1 m.s^{-2} (vapos_95) parameters are good indicators for classifying of driving styles in real driving conditions (Gallus et al., 2016; Gallus et al., 2017).

Interest is growing in using vehicular jerk to quantitatively represent driving volatility (Wang et al., 2015) in order to capture the variations in instantaneous driving decisions. While acceleration characterizes changes in speed, vehicular jerk characterizes how a driver changes the acceleration or deceleration (Liu et al., 2017). The study performed by Liu et al. (2017) found that driving volatility is characterized by hard accelerations/braking, lane changes/turns, and unusually high speeds for roadway conditions. Wang et al. (2015) and Feng et al. (2017) concluded that the frequency of large positive jerk is an important metric of driving volatility. Specific thresholds of positive and negative vehicular jerk per speed were developed (Liu et al., 2014; Khattak et al., 2015; Wang et al., 2015). Other authors (Feng et al., 2017; Khattak & Wali, 2017; Kamrani et al., 2018) have examined the relationship between volatility and frequency of crashes.

However, the relationship between driving volatility and emissions is a subject poorly explored. Main factors that affect fuel consumption and emissions can be divided into the following categories: vehicle characteristics (including, speed, acceleration, or loading), road conditions and environment. The existing studies on driving behavior have demonstrated that pollutant emissions and fuel consumption vary between different speed ranges. Hence, eco-driving research has been mostly focused on the optimization of driving behavior (Kim & Choi, 2013; Liu, Xie, Ma & Chen, 2014; Son et al., 2016; Toledo & Shiftan, 2016; Jeffreys et al., 2018). The identification of anomalous driving as means of warning information for drivers can be useful in connected vehicle applications. While research on fuel consumption and pollutant emissions in connected vehicles is well-documented (Garceau et al., 2013; Liu et al., 2015; Astarita et al., 2019; Shao et al., 2019), few studies have addressed the relationship between vehicular jerk and fuel consumption in rural, urban and highway roads (Huang & Peng, 2017; Zhang et al., 2020; Fernandes et al., 2021), and exhaust emissions in suburban areas (Fernandes et al., 2020).

Recent studies have investigated the relationship between volatility and crash propensity in naturalistic driving environments. For instance, Kim et al. (2016) stated that there exist a strong association between rear-end crash rates and tendency of hard decelerations with values between -4 and -3 m.s^{-2} . Naturalistic driving is useful to study road traffic crashes, however, acceleration and jerk correlation or even study of crash propensity at school zones leads to random heterogeneity (Wali et al., 2018; Wali, Khattak & Karnowski, 2019; Wali & Khattak, 2020). Arvin et al. (2019) applied probit models to show the correlation between distracted and aggressive driving and crash intensity. Wali et al. (2020) investigated how driving volatility in time to collision links to crash-injury severity, and they found that a greater driving volatility in time to collision increased the severity of crash events. However, these works did not assess the impacts of driving volatility on vehicular emissions. Liu et al. (2020) used Bayesian Hierarchical models to examine the grade impact on vehicle speed and acceleration. This work neither assessed the impact of those parameters on vehicular emissions nor included a detailed safety analysis.

The motivation of this article is to explore a driving volatility concept for assessing emissions in light duty vehicles (LDVs) and driving behavior style classification using different metrics. It is hypothesized that jerk and acceleration thresholds were good indicators of the driving behavior style classification. Also, vehicular jerk is expected to be good threshold of on-road carbon dioxide (CO_2) and NO_x emissions, regardless of the driving conditions, vehicle characteristics and route type. These assumptions were tested in one partly urban/rural route and two highway routes using dynamic, engine, and on-road emission second-by-second data of different LDVs with naturalistic driving.

Therefore, the specific objectives are two-fold: (1) to explore driving behavior classification using vehicular jerk and acceleration thresholds with those based on RPA, MPA, and power demand; and (2) to assess the influence of vehicular jerk on trip-specific CO_2 and NO_x emissions.

2. Methodology

The core idea of the proposed methodology is to develop an empirical framework using a complete naturalistic driving to assess vehicle emissions along three alternative routes from a real origin-destination pair. The methodology proceeded in three main steps, as depicted in **Figure 1**. First, on-road emissions, engine and location data were collected in the studied location followed by the exploratory analysis using Spearman correlation, linear regression, Principal Component Analysis (PCA), and then ANOVA. Finally, a driving volatility analysis was performed.

Figure 1: Methodology overview.

2.1. Data collection

Data collection were carried out in Aveiro Region (Portugal), along two highways (A1 and A29) and one partly urban/rural (N109) routes in both directions. A1 and A29 have different traffic volumes, road grade, and tolling systems while N109 is a national road partly conducted on a rural (63%) and urban (37%) roads. These routes were previously analyzed in terms of both crash frequency and location by Fernandes et al. (2019a) from 2015 to 2017. It was observed that 47% of crashes occurred at rural road sections of N109 and almost half of light injuries were observed in highways. Figure 2 illustrates road grade frequency by route. The road gradient classification was based on the research by Franco et al. (2014). It can be seen that highway routes have different slope distributions, especially in extreme values. Strong downhill and strong uphill represented together 30%, 40%, and 50% of the N109, A1, and A29 length, respectively. Almost 23% of N109 is on flat road sections.

Figure 2: Road gradient for route 1 (A1), route 2 (A29) and route 3 (N109).

Table 1: Technical specifications of the tested vehicles.

Vehicle Id	c1	c2	c3	c4
Year	2006	2017	2017	2018
Emission Standard	Euro 4	Euro 6b	Euro 6b	Euro 6b
Engine Displacement (L)	1.8	1.3	1.6	1.5
Horsepower (Hp)	125	75	98	90
Odometer reading at test start (km)	180,000	32,000	23,000	25,000
Category	Multi-purpose	Small	Small	Small

Table 2: Descriptive Statistics regarding each vehicle record.

Route/Driver		Route 1 - A1				Route 2 - A29				Route 3 - N109			
		C1	C 2	C 3	C 4	C 1	C 2	C 3	C 4	C 1	C 2	C 3	C 4
Parameter	# of trips	2	2	1	2	4	2	2	2	5	4	3	4
speed (km/h)	mean	123	101	123	114	116	105	130	109	46	43	37	46
	std	11	7	19	6	9	5	13	13	18	14	19	15
acceleration (m/s ²)	min	-1.11	-0.83	-1.11	-1.94	-2.78	-1.39	-1.39	-1.37	-4.72	-4.44	-3.33	-5.56
	max	1.94	0.83	0.83	1.94	1.67	0.83	1.39	2.22	5.00	3.89	2.78	5.56
	std	0.36	0.18	0.36	0.32	0.30	0.22	0.34	0.32	0.66	0.52	0.55	0.58
jerk (m/s ³)	min	-1.67	-0.83	-1.11	-1.94	-1.94	-1.39	-1.39	-1.39	-5.00	-3.89	-3.33	-3.61
	max	1.11	0.83	1.11	1.94	1.94	1.39	1.39	1.39	4.72	3.89	3.06	5.56
	std	0.35	0.21	0.38	0.33	0.30	0.24	0.30	0.29	0.57	0.48	0.50	0.49
NOX (g/km)	mean	4.97	2.17	2.32	2.20	2.80	2.23	4.31	1.82	1.55	2.09	0.41	1.56
	std	0.20	0.20	-	1.15	1.17	0.45	1.82	0.09	0.53	0.55	0.17	0.36
CO2 (g/km)	mean	324	170	202	180	263	183	279	174	258	151	146	132
	std	23	4	-	37	45	1	29	2	63	40	1	12
fuel (L/100km)	mean	12.18	6.38	7.29	6.75	9.85	6.84	10.38	6.47	8.9	5.38	4.41	4.65
	std	4.42	1.53	3.86	2.28	3.44	2.73	3.29	1.95	6.11	3.61	3.24	2.75
RPM	mean	2517	2104	2286	2111	2313	2191	2418	2007	1595	1303	1275	1369

	std	356	140	356	119	192	112	224	258	362	262	312	319
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2.2 Explanatory Analysis

2.2.1. Spearman Correlation

This section uses the Spearman correlation to measure the strength of a monotonic relationship between dynamic, engine, energy and emission parameters obtained from the database. **Table 3** summarizes the main results for the speed, acceleration, CO₂, NO_x, engine revolutions per minute (RPM) and fuel consumption for motorway routes and all routes. Approximately 94% and 88% of the samples on motorways and all routes, respectively, have a strong correlation (> 0.7) between NO_x and CO₂. As expected, fuel consumption is strong correlated with CO₂ in more than 70% of samples on motorways but not with NO_x, which is in concordance with previous literature (Fontaras, Zacharof & Ciuffo, 2017). The amount of CO₂ emissions and fuel consumption depends on several parameters such as type of vehicle, driving behavior, road and engine characteristics. NO_x emissions in diesel vehicles depend not only on engine load and engine revolution, but also on the exhaust after-treatment system, such as Lean NO_x Trap and Selective Catalytic Reduction (Giechaskiel et al., 2014; Johnson, 2016; Bai, Chen, Sun, Wang and Li, 2017). These after-treatment systems have been contributing to less emission amounts in recent vehicles, thereby explaining the high NO_x-fuel relation in Euro 4 (~18%) compared to Euro 6 b (~5%). In contrast, RPM and Altitude show a strong correlation in only 6% and 3% of motorway and all route trips, respectively.

Table 3: Spearman correlation coefficients between variables for the entire database.

Pair	Motorways	Total	
		Euro 4	Euro 6b
NO _x -CO ₂	94%	100%	81%
RPM-speed	59%	18%	63%
Fuel consumption-CO ₂	71%	27%	41%
Fuel consumption-NO _x	18%	18%	5%
Fuel consumption-acceleration	47%	18%	9%
RPM-NO _x	6%	9%	0%
Altitude-NO _x	6%	0%	5%

2.2.2. Linear Regression

To explore the data variability and reinforce Spearman's correlation results, scatter plots were analyzed and compared to linear regression results. After that, PCA was performed based on routes and vehicles.

All equations are listed in **Tables S1** (in the supplementary data file) and **Table 4**. To avoid presenting a dense document, scatter plots for speed versus CO₂, NO_x, RPM, fuel consumption and altitude are only displayed for route A29 and vehicle c2. This choice is supported by the best adjusted R² for routes (0.72) and vehicles (0.91) found in **Table 4**. The other plots are displayed in the supplementary data file in **Figures S2 to S5**.

Table 4: Linear regression between speed with: CO₂, NO_x, VSP mode, RPM, Fuel consumption and altitude.

	ID	model	p-value	Adjusted R2
Route	A1	$y=39.269+0.9397x_1+0.7169x_3+0.0329x_4-0.4129x_5-0.0544x_6$	0	0.637
	A29	$y=33.104+1.4416x_1+20.4580x_2+0.0804x_3+0.0322x_4-0.6250x_5$	0	0.720
	N109	$y=2.2943+99.3040x_2+0.01158x_3+0.0310x_4-0.3235x_5-0.0910x_6$	0	0.505
Driver	C1	$y=-25.0580+1.5088x_1+29.2630x_2+0.3007x_3+0.0390x_4-0.4682x_5-0.4107x_6$	0	0.826
	C2	$y=-23.9650+1.2696x_1+0.1189x_3+0.0485x_4-0.5044x_5+0.2121x_6$	0	0.912
	C3	$y=-25.5230+2.3621x_1+32.3180x_2+0.0459x_4-0.5736x_5+0.2506x_6$	0	0.906
	C4	$y=-11.2970+4.2241x_1-47.4110x_2+0.2016x_3+0.0349x_4-0.3238x_5+0.3482x_6$	0	0.832

The relationships between five driving behaviors (from ten identified) are analyzed using the scatter plot of A29 in **Figure 3 a-c**. For example, for the driving behavior t1a29c12 (direction south-north of vehicle 1 (for the second trip) on motorway A29), a more aggressive behavior is observed from both speed-CO₂ and speed-fuel ratio relationships. In addition, high emissions are seen in the speed-NO_x ratio for driver t1a29c1. A linear relationship between RPM and speed was observed (**Figure 3-c**), which is explained by the transmission type of vehicles (manual). It can be noted that some variables, such as RPM, CO₂ and NO_x can identify five different driving behaviors. **Figure 3 d-e** revealed that the relationship between speed-fuel consumption and speed-altitude does not exhibit different driving behaviors. From the graphical observation of **Figure 4** for vehicle c2, there is a clear separation of the motorway from rural environment in all pair of variables displayed. There is a spectrum of the data exhibiting higher CO₂ and NO_x emissions per unit distance for motorways, where is possible to identify four different driving behaviors (**Figure 4 a -b**). The analysis of **Figure 4** also showed a high range of fuel consumption per unit distance values at low to moderate speeds, which is mostly

explained by acceleration episodes at urban environment, for instance, vehicle leaving a roundabout and/or a signalized intersection after stopping at a red signal. These range of fuel consumption values can be also observed on the other vehicles. In summary, all models based on speed have a good adjusted R^2 , but a linear model is found to be not suitable to study the variability of the data. In fact, linear relationship is only exhibited in the case of RPM-speed. Since the explained variability from data sets is important to establish visual conclusions, and from Spearman correlations, some different pairs of correlations were found, a multivariate statistical analysis can be used.

a)

b)

c)

d)

e)

Figure 3: Scatter plot of instantaneous speed together: a) CO₂, b) NO_x, c) Fuel Consumption, d) RPM and e) altitude for Route A29.

a)

b)

c)

d)

e)

Figure 4: Scatter plot for vehicle c2 of instantaneous speed together: a) CO₂, b) NO_x, c) Fuel Consumption, d) RPM and e) altitude.

2.2.3. Principal Component Analysis

PCA is a statistical multivariate technique that allows to reduce the original set of variables ($X_1, X_2, \dots, X_p$), in a smaller set of non-correlated variables called principal components PCs ($Y_1, Y_2, \dots, Y_p$), in order to represent the largest information, thus

explaining the maximum variability of the original set of variables. Each principal component is a linear combination of the original variables $\mathbf{X}$ constructed by means of linear combinations with the largest variance and ensures that all PCs are orthogonal to each other. Therefore, no redundant information is found. While p components are mandatory to reproduce the total system variability, commonly this variability can be described by a small number k of principal components. It is expected that the representation of individuals in the reduced subspace defined by the first PCs (first two or three to plot in 2D or 3D, respectively) will let to discover relationships and properties between them. All details of computation and proofs can be consulted in Chapter 8 of (Johnson and Wichern, 2007).

Let X_1 as speed, X_2 as jerk, X_3 as CO_2 , X_4 as NO_x , X_5 as VSP mode, X_6 as RPM, X_7 as Fuel flow rate and X_8 as altitude. From **Table 5**, it can be noted that more than 99% of data variability is explained by only the first two PCs for both routes and vehicles data sets. Since other components in each model absorb less than 0.25% of the variability, one can consider that the new variables Y_1 and Y_2 can replace the original eight variables without relevant loss of information, meaning that the subsequent conclusions remain strong.

Table 5: Summary of explained variance using the first two principal components.

ID	A1	A29	N109	C1	C2	C3	C4
CP1	99.49	99.54	99.59	99.60	99.73	99.77	99.51
CP2	0.38	0.27	0.21	0.25	0.20	0.13	0.30
Total	99.87	99.81	99.80	99.85	99.93	99.90	99.81

The reduced models with only the first two components are described in **Table 6**. The construction of the principal components revealed that the highest coefficients are those with higher variance on corresponding variables, and thus they are more correlated with the associated principal component. A close analysis of **Table 6** shows that the variable X_6 (RPM) is positive and highly correlated with PC1, regardless of the type of route. Concerning the PC2, the variable X_8 (altitude) is the one that most contributes at motorways, while the variable X_7 (fuel consumption) shows to have the highest contribution at the national roads. From the analysis of the vehicles, it seems that PC1 is mostly explained by the variable X_6 (RPM), but CP2 is explained beyond X_8 (altitude) and X_1 (speed).

Table 6: Reduced models with the first two principal components for each route and vehicle.

	ID	model
Route	A1	$Y_1 = 0.0359X_1 + 0.0080X_3 + 0.0002X_4 + 0.0022X_5 + \mathbf{0.9992}X_6 + 0.0080X_7 + 0.0148X_8$
		$Y_2 = -0.0509X_1 + 0.0001X_2 + 0.0216X_3 + 0.0008X_4 + 0.0155X_5 - 0.0132X_6 + 0.0135X_7 + \mathbf{0.9982}X_8$
	A29	$Y_1 = 0.0429X_1 + 0.0080X_3 + 0.0002X_4 + 0.0030X_5 + \mathbf{0.9990}X_6 + 0.0072X_7 - 0.0024X_8$

Driver	N109	$Y_2=0.1336X_1+0.0331X_3+0.0007X_4+0.0408X_5-0.0036X_6-0.0259X_7+\mathbf{0.9893}X_8$
		$Y_1=0.0321X_1+0.0026X_3+0.0021X_5+\mathbf{0.9995}X_6+0.0013X_7-0.0014X_8$
		$Y_2=-0.6057X_1+0.0044X_2+0.0096X_3+0.0243X_5+0.0184X_6+\mathbf{0.7936}X_7+0.0469X_8$
	C1	$Y_1=0.0632X_1+0.0058X_3+0.0001X_4+0.0039X_5+\mathbf{0.9974}X_6+0.0033X_7+0.0323X_8$
		$Y_2=\mathbf{0.7252}X_1-0.0005X_2+0.0440X_3+0.0009X_4+0.0121X_5-0.0673X_6-0.1615X_7+\mathbf{0.6644}X_8$
	C2	$Y_1=0.0620X_1+0.0032X_3+0.0028X_5+\mathbf{0.9973}X_6-0.0017X_7+0.0399X_8$
		$Y_2=0.3225X_1-0.0003X_2+0.0272X_3+0.0004X_4+0.0178X_5-0.0579X_6-0.0520X_7+\mathbf{0.9428}X_8$
	C3	$Y_1=0.0710X_1+0.0061X_3+0.0001X_4+0.0037X_5+\mathbf{0.9970}X_6+0.0013X_7+0.0314X_8$
		$Y_2=\mathbf{0.6564}X_1-0.0002X_2+0.0445X_3+0.0007X_4+0.0116X_5-0.0702X_6-0.1195X_7+\mathbf{0.7401}X_8$
	C4	$Y_1=0.0638X_1+0.0037X_3+0.0034X_5+\mathbf{0.9972}X_6-0.0033X_7+0.0388X_8$
		$Y_2=\mathbf{0.6071}X_1-0.0004X_2+0.0337X_3+0.0005X_4+0.0243X_5-0.0699X_6-0.0565X_7+\mathbf{0.7884}X_8$

The plots of the PCA (**Figures 5 and 6**) exhibit several driving behaviors concerning the routes and vehicles. Again, only route A29 (**Figure 5**) and vehicle c2 (**Figure 6**) data are shown in the main manuscript while the remaining graphs (**Figures S6 to S10**) can be found in the supplementary data file. From motorways, three different clusters of driving behavior can be considered, as shown in **Figure 5** and **Figure S6**. These clusters are represented as solid, dashed and dot lines. As for the scatter plots, PCA plot is not able for identifying driving profiles in the case of the national road (see **Figure S7**). A close view to the solid line cluster of **Figure 5** allows to associate data with high speed and CO₂ and NO_x emission rates (see **Figures 3 a-b**), thus indicating a cluster of aggressive behavior.

The graphical analysis of PCA for vehicles data sets indicates different driving behaviors, namely at motorway trips, as depicted in **Figures 6** and **Figures S8-S10**. There is a clear separation between motorways and national road data, and in some cases, it is even possible to distinguish route A1 from route A29 data.

Figure 5: Principal Component Analysis using the first two principal components with total of 99.81% of explained variability regarding route A29.

Figure 6: Principal Component Analysis using the first two principal components with total of 99.93% of explained variability regarding vehicle c2.

2.2.4. ANOVA

Since the focus of this paper is to classify the type of driving pattern and its impact on exhaust emissions, it is important to understand which metrics are more suitable for that purpose. To assess the significance of the effect of variation in selected variables (speed, acceleration, vehicular jerk, CO₂, NO_x, Vehicle Specific Power – VSP (Frey, Unal & Chen, 2002), RPM and fuel consumption) on variation in route types by traveling direction (T1: south-north and T2: north-south) and without the influence of the vehicle category, analysis of variance (ANOVA) was performed. The variation of the mentioned parameters (and the range of the changes) can be used as a safety indicator to better explain the safety concerns that results from driving behavior. Kruskal-Wallis nonparametric test, with level of significance 5% was used to determine if there are statistically significant differences between vehicles for each variable and route (Weaver, Morales, Dunn, Godde & Weaver, 2017). The results indicated that acceleration and vehicular jerk test values were higher than the critical value, as shown in **Table 7**, which means that there exist indeed significant differences between vehicles/drivers for the acceleration and vehicular jerk. Accordingly, acceleration and vehicular jerk can be considered as driving style parameters regardless of the route type. Although driving behavior can be analyzed based on acceleration, RPA and MPA, vehicular jerk is focused on the changes of acceleration/deceleration rate in a specific period based on instantaneous decision maneuvers. The main advantage of the use of vehicular jerk is that driver instantaneous behavior is described for different acceleration and deceleration patterns over the time, for instance, acceleration followed by acceleration or deceleration, deceleration followed by deceleration and acceleration, alternate accelerations or decelerations, constant accelerations or constant decelerations, and cruise speeds (Zhang et al, 2020). This extra information is not given by RPA or MPA acceleration-based parameters.

Table 7: *p*-value for Kruskal-Wallis results for all roads.

Variable	T1 A1	T1 A29	T1 N109	T2 A1	T2 A29	T2 N109
Speed	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Acceleration	0.7286	0.8175	0.0935	0.2641	0.1791	0.0727
Jerk	0.9449	0.9957	0.9990	0.8841	0.9990	0.9970
CO ₂	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
NO _x	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
VSP mode	0.0003	0.0012	0.0134	0.0000	0.0000	0.0019
RPM	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Fuel consumption	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

Note: T1 is the north-south direction and T2 is the south-north direction

Wang et al. (2015) proposed six different vehicular jerk patterns to construct a driving volatility score. These modes are set of three consecutive seconds and they are defined as acceleration-deceleration lower acceleration, higher acceleration, deceleration or lower deceleration, higher deceleration, and acceleration at these moments. They highlighted that there can be a greater chance of collisions when negative vehicular jerk occurs compared with positive vehicular jerk. When vehicles are followed by other vehicles, negative vehicular jerks can result in sudden shortening of distance between the vehicles and following ones, perhaps creating a shockwave. In section 3.3, vehicular jerk frequency, range and impacts on tailpipe emissions are examined in detail.

2.3. Classification of driving style

Although vehicular jerk is derived from acceleration, both kinematic parameters were used in this case. This is due to the fact that the probability of a crash between two vehicles increases for negative vehicular jerk values in the leading vehicle, thus resulting in lower braking distances (Liu et al., 2015; Wang et al., 2015). The acceleration threshold for driving behavior classification used by Deligianni et al. (2017) was established using rigorous statistical models using multilevel mixed effects. The jerk threshold for safety and comfort for passengers was set to be under 0.9 m.s^{-3} by Kiliç and Baybura (2012). Regarding acceleration thresholds, Choi and Kim (2017) applied regression techniques to demonstrate that these values have a positive effect in increase of fuel consumption and CO₂ emissions. In a research conducted by Bärghman et al (2017), risky driving behaviors such as, speeding, close following and harsh braking were evaluated through descriptive statistics of data and questionnaires. Speeding is defined as “travelling at least 11% over the speed limit for more than 10 seconds”. In this study, the proposed driving style classification is constructed based on several thresholds presented in **Table 8**. The definitions of the driving behavior are the same as Gallus et al. (2017) work, i.e., aggressive, normal severe and calm.

- aggressive: 3 or 4 thresholds failure;
- normal severe: 1 or 2 thresholds failure;
- calm: none thresholds failure.

Table 8: Parameters thresholds of the driving style.

Parameter	Reference	Values	Notes
jerk (m.s ⁻³)	Kiliç and Baybura (2012)	0.9	-
maximum acceleration (m.s ⁻²)	Choi and Kim (2017)	1.47	motorways
		2.16	urban and rural
maximum deceleration (m.s ⁻²)	Deligianni et al. (2017)	3.4	-
Time speed limit exceed more than 10 seconds	Bärgman et al. (2017)	11%-15%	light speeding
		16%-20 %	severe speeding
		more than 21%	extreme speeding
MPA (m.s ⁻²)	(Grunditz, 2014)	0.4	Urban
		0.4	Rural
		0.3	Motorway
RPA (m.s ⁻²)	(Grunditz, 2014)	0.2	Urban
		0.14	Rural
		0.12	Motorway

As mentioned before, RPA (Gallus et al., 2017), MPA (Gallus et al., 2017; Fernandes et al., 2019 b) and power demand (Frey et al., 2002) can be used to assess driving behavior. RPA and MPA are based on positive acceleration values (a_i^+) higher than 0.1 m.s⁻² and computed using Equation 1 (EC, 2016):

$$a_i = \frac{v_{i+1} - v_{i-1}}{2 \times 3.6} \quad (1)$$

where v_{i+1} and v_{i-1} are the instantaneous vehicle speed (km.h⁻¹) in the second of travel $i-1$ and $i+1$, respectively.

RPA and MPA were then calculated (EC, 2016) using Equations 2 and 3, respectively:

$$RPA = \frac{\sum_{i=1}^n \frac{v_i}{3.6} a_i^+}{d} \quad (2)$$

$$MPA = average(a_i^+) \quad (3)$$

where v_i is the instantaneous vehicle speed in the second of travel i (km.h⁻¹) and d represents the total distance of the route (m).

Table 8 lists RPA and MPA thresholds by road type according to the Worldwide harmonized Light duty driving Test Cycle (WLTC). It must be emphasized that the classification of driving varied according to the type of road, which means that a same driver may have a different driving style.

Power demand is the product of the average speed and acceleration, and it shows to be a proper parameter to classify different levels of emissions (Frey et al., 2002; Choi & Kim, 2017). Franco et al. (2014) considers a set point as the threshold between mild and strong of 9.2 m².s⁻³ based on the New European Driving Cycle (NEDC), but research team uses the set point of 21.01 m².s⁻³ according to the WLTC (Kühlwein, German & Bandivadekar, 2014), as follows:

- strong negative: $v \times a < -21.01 \text{ m}^2.\text{s}^{-3}$
- mild negative: $-21.01 < v \times a < 0 \text{ m}^2.\text{s}^{-3}$
- mild positive: $0 < v \times a < 21.01 \text{ m}^2.\text{s}^{-3}$
- strong positive: if $v \times a > 21.01 \text{ m}^2.\text{s}^{-3}$

3. Results

3.1. RPA and MPA

Figure 7 a-f depicts RPA and MPA values with driving style classification (aggressive, normal severe and calm) by route type (A1, A29 and N109) and vehicles (c1, c2, c3 and c4). Both parameters indicated a good differentiation in driving style classification for highway routes, except c1 along A29 that recorded RPA and MPA values lower than WLTC thresholds while classified as aggressive (red bars). The comparison of highway routes showed higher RPA and MPA values in A1 mostly due to its high traffic volume that was approximately three times more than A29 (IMT, 2019), thus resulting in more overtaking maneuvers and increasing the probability of crashes. Results also confirmed that the lowest RPA and MPA values were obtained for vehicle c2, which had been classified as calm. Regarding the N109, some acceleration-based parameters did not represent the differences in driving styles as prior routes did (see **Figures 7-e and f**). For example, some c2 trips were classified as aggressive while their RPA and MPA values were lower than those classified as normal severe.

a)

b)

Figure 7: RPA and MPA with driving style classification by route: a) RPA for A1; b) MPA for A1; c) RPA for A29; d) MPA for A29; e) RPA for N109; and f) MPA for N109.

3.2.Power demand

Figure 8a-c displays the mass power frequency in terms of classification type and by route. Mild positive was the most representative driving style regardless of the vehicle and route, but some differences were observed among routes. While strong positive and negative mass power accounted together up to 9% at the A1, their contribution decreased to less than 2% and 1% on A29 and N109, respectively. The graphs bars revealed that the

distribution of mass power frequency was similar among vehicles, but c2 yielded very strong positive and negative values (0.32-0.5%, depending on the route).

a)

b)

c)

Figure 8: Mass Power frequency by route: a) A1; b) A29; and c) N109.

From **Figure 9**, it can be noted that strong positive power demand was associated with highest amount of CO₂ emissions per unit distance in A1 (1.5-2.5 times higher than the average values of the other classes, depending on the vehicle) and A29 (0.75-3 times higher than the average values of the other classes, depending on the vehicle). A close look to A29 values revealed that small-sized c2 was more sensitive to strong positive power demand than c4, which is mostly explained by the low horsepower of c2 (see **Table 1**). The analysis of N109 in c1 showed CO₂ values 2.5 times higher in strong positive than the other classes while c2 and c3 obtained the highest CO₂ values in strong positive (more than 10% higher the average values) and mild positive classes (12% higher than the average values), respectively.

a)

b)

c)

Figure 9: Accumulated CO₂ (g/km) by power demand and route: a) A1; b) A29; and c) N109.

All vehicles recorded the highest amount of NO_x emissions per unit distance in strong positive class along A1, as exhibited in **Figure 10**. This class had on average an accumulated NO_x between 24% and 46% for c3 and c1, respectively, higher than the average values of other classes. The results for A29 were similar to A1, but the differences between extreme values were much higher; 6 and 2 times higher than the average values in c2 and c4, respectively. The driving c1 was sensitive to strong positive power demand along N109 with NO_x increased up to 1.5 g.km⁻¹, but c3 and c4 achieved similar NO_x values among classes of power demand. This happens because almost all vehicles were not subjected to maximum power demand along route.

a)

b)

c)

Figure 10: Accumulated NOx (g/km) by power demand and route: a) A1; b) A29; and c) N109.

Above results suggest an impact of positive power demand on global and local pollutant emissions, as demonstrated by previous studies (Frey et al., 2002; Choi & Kim, 2017). To complement the analysis, **Table 9** compares CO₂ and NOx emission results using the threshold of 21.01 m².s⁻³ and the threshold value of m².s⁻³ proposed by Frey et al. (2002) by vehicle and route. The resulting emissions per unit distance were equal in both thresholds for several trips, such as c4 along A1 and A29, c2 along A29 and all vehicles along N109. For the remaining cases, the differences were found to be small (4% to 9%, depending on the vehicle and the pollutant). The proposed threshold by Frey et al. (2002) was thus shown as a proper value for driving style classification in different types of roads.

Table 9: Emission results for different power demand thresholds by vehicle and by route.

Route	Vehicle	CO2 (g.km ⁻¹)		NOx (g.km ⁻¹)	
		$v \times a = 21.01$	$v \times a = 21.58$	$v \times a = 21.01$	$v \times a = 21.58$
A1	c1	478	499	7.01	7.31
	c3	354	368	2.88	2.19
	c4	346	346	4.29	4.29
A29	c1	297	271	2.71	2.6
	c2	397	397	12.47	12.47
	c4	265	265	4.16	4.16
N109	c1	484	484	1.61	1.61
	c2	27	27	0.39	0.39
	C3	165	165	0.38	0.38

3.3. Vehicular jerk

Figure 11 a-c displays the percent of time spent in each jerk class in 0.5-m.s⁻³ time-intervals, by route type. It was found that the frequency of negative jerks in A1 was higher

than A29, regardless of the vehicle type; they accounted for about 29% and 27% of total jerk in A1 and A29, respectively. A detailed analysis of both motorways showed high frequencies of zero jerk in c2 and c4 (>70%) when compared to the remaining cases. Interestingly, N109 covered wider range of jerk classes (from -3.5 m.s^{-3} to 4 m.s^{-3}) than highway routes (**Figure 7-c**). This was due to the fact that drivers were continuously pressuring pedals (as a result of changing in acceleration and deceleration rates) near traffic lights, roundabouts and crosswalks, as well as some overtaking maneuvers during the trips. It was also found that the crash probability in N109 can be higher than other routes due to the wider range of jerk values, which is in line with crash recording at the studied locations (see Section 2.1. for those details). However, the crash severity in A1 and A29 can be higher than those obtained in N109, mostly due to the wide range of speed, acceleration/deceleration or vehicular jerk.

a)

b)

c)

Figure 11: Jerk range frequency by route: a) A1; b) A29; and c) N109.

The higher accumulated CO₂ emissions per unit distance in highways were generated in extreme jerk classes, as exhibited in **Figure 12 a-b**. For example, c1 accumulated CO₂ per unit distance in jerk classes of -1.5 m.s⁻³ and 1.0 m.s⁻³ was two times higher than the accumulated values achieved in other classes. In contrast, almost all vehicles yielded the lowest accumulated CO₂ per unit distance in jerk class of 0 m.s⁻³ in both motorway routes. The distribution of jerk versus CO₂ varied among drivers; the difference between extreme A29-CO₂ accumulated values was much lower in c2 than did c4 along A29. These results are pertinent since some c2 trips were associate with calm driving (see **Section 3.1**). Analysis of N109 indicated that the distribution of accumulated CO₂ by jerk class was dissimilar regarding to prior routes, as depicted in **Figure 12-c**. All vehicles produced the higher level of CO₂ in jerk classes higher than the threshold value of 0.9 m.s⁻³ (0-80% higher than the average CO₂ trip, depending on vehicle). For jerk classes between -1.5 and 1.0 m.s⁻³, the resulting accumulated CO₂ little varied for the same driver.

a)

b)

c)

Figure 12: Accumulated CO₂ (g/km) by jerk range frequency and by route: a) A1; b) A29 and c) N109.

Figure 13 a-c shows the distribution of NO_x values per unit distance and jerk class by route type. Main results suggested similar jerk distributions to CO₂ values, which is expected since the analysis of CO₂ and NO_x showed positive correlation between these variables. Almost all vehicles produced the highest level of accumulated NO_x in extreme positive jerk classes ($> 1 \text{ m.s}^{-3}$) (0-25% higher than the average trip value, depending on the vehicle and route). The values near zero jerk had the lowest accumulated NO_x values, regardless of the vehicle. For jerk classes between -1.5 and 1.0 m. s⁻³, the range of NO_x values was not high, especially in N109.

a)

b)

c)

Figure 13: Accumulated NO_x (g/km) by jerk range frequency and by route: a) A1; b) A29; and c) N109.

The analysis of **Figure 12 and 13** seems to confirm from an increasing trend from negative to null jerk values in CO₂ and NO_x in several trips. Thus, driving volatility could have an important effect on emission levels. According to Wang et al. (2015) and Kamrani et al (2018), negative jerk during positive accelerations can be defined as volatility driving with clear implications in safety. To understand this relationship, the average CO₂ and NO_x emission values per unit distance were computed for negative jerk values with positive acceleration values in the previous 4 seconds¹, as listed in **Table 10**. Although the results are only displayed for c1, other vehicles recorded identical values among jerk time series. Both CO₂ and NO_x were much higher than values obtained in zero jerk values (on average 7%-18% higher than CO₂ and NO_x average values, depending on the vehicle and route). This confirms the hypothesis on what concerns to the vehicular jerk be a good indicator of on-road emissions, regardless of the driving conditions, vehicle characteristics and route type.

Table 10: Emissions values for negative jerk (time i) and positive acceleration for the previous 4 seconds.

Route	jerk < 0	CO ₂ (g.km ⁻¹)	NO _x (g.km ⁻¹)
A1	$a_{i*1} > 0$	351	5.33
	$a_{i*2} > 0$	339	5.14
	$a_{i*3} > 0$	330	4.93
	$a_{i*4} > 0$	323	5.03
A29	$a_{i*1} > 0$	237	1.97
	$a_{i*2} > 0$	236	2.01
	$a_{i*3} > 0$	241	2.00
	$a_{i*4} > 0$	215	1.86
N109	$a_{i*1} > 0$	249	1.00
	$a_{i*2} > 0$	267	1.02
	$a_{i*3} > 0$	269	1.11

¹There is a possibility of a delay from one to two seconds of recorded emissions with the respective value of acceleration. Therefore, with this phenomenon plus the jerk definition, the computation was made until the previous four seconds.

	$a_{i*4} > 0$	249	0.98
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Figures 14 to 16 plot CO₂ and NO_x emission rates, and vehicular jerk and acceleration over the time for the most volatile driver (c1). The horizontal solid line represents the jerk and acceleration safety thresholds for each graph. With respect to A1, the thresholds of jerk, maximum acceleration and minimum acceleration were exceeded in 2%, 2% and 3% of the trip time, respectively. For jerk values higher than 0.9 m.s⁻³, CO₂ and NO_x emission rates increased up to 15 g.s⁻¹ and 0.4 g.s⁻¹, respectively. The plots also showed emission peaks from negative to null jerk values in positive acceleration, which confirmed the results in **Table 10**. **Figure 15** indicates that violations in jerk thresholds accounted for only 2% (8 seconds) of the trip time, which is mostly explained by low traffic volume in this route. It must be also outlined that driver rarely attained the maximum and minimum accelerations (less than 0.5% of the trip time). Concerning the N109, the total time above jerk threshold was 24 seconds, which represented just 3% of trip time (see **Figure 16**). The CO₂ and NO_x emissions were 10 g.s⁻¹ and 0.06 g.s⁻¹ higher than the average trip values, respectively. Emission peaks can be seen from negative to null jerks, but these were more sensitive in NO_x than for CO₂. The analysis of other vehicles resulted in similar conclusions to c1.

c)

d)

Figure 14: Jerk and acceleration profiles versus emissions for driver 1 in A1: a) acceleration versus CO₂; b) jerk versus CO₂; c) acceleration versus NO_x; and d) jerk versus NO_x.

a)

b)

c)

d)

Figure 15: Jerk and acceleration profiles versus emissions for driver 1 in A29: a) acceleration versus CO₂; b) jerk versus CO₂; c) acceleration versus NO_x; and d) jerk versus NO_x.

a)

b)

c)

d)

Figure 16: Jerk and acceleration profiles versus emissions for driver 1 in N109: a) acceleration versus CO₂; b) jerk versus CO₂; c) acceleration versus NO_x; and d) jerk versus NO_x.

4. Conclusions and Future work

This research used a driving volatility analysis to assess exhaust emissions and driving style classification. For this purpose, data were collected from four light duty vehicles, and considering different driving styles and road conditions. An explanatory correlation of dynamic, engine, energy and emission parameters were conducted. Scatter plots showed that speed performed better in detecting vehicular emissions on motorways. Furthermore, the PCA multivariate statistical technique enabled to distinguish different driving behaviors and well-separated between motorways and national road data. More than 99% of total variability was explained by retaining only the first two principal components where RPM, speed and altitude were the most contributing variables in explaining the variability in all the data sets. After that, a driving behavior classification was done using RPA and MPA acceleration-based parameters, and power demand thresholds followed by a relationship between vehicular jerk and acceleration thresholds and on-road exhaust emissions.

The findings showed both RPA and MAP metrics allowed a good differentiation into calm, normal and severe trips in motorway roads. However, some urban/rural trips classified as aggressive were resulted in RPA and MPA lower than normal severe trip values. The classification of driving style based on power demand using WLTC thresholds also showed to be proper for assessing on-road CO₂ and NO_x emissions, regardless of the route type.

The comparison of jerk classes and emissions per unit distance indicated that the accumulated CO₂ and NO_x significantly increased from negative to null jerk values, and that the peak of the emissions occurred at negative vehicular jerks during the positive acceleration. The latter situation is defined as risky behavior since vehicular jerk, acceleration and deceleration were above the identified thresholds in the literature. Thus, the use of driving volatility based on vehicular jerk can be useful for identifying differences in the emissions amounts in different type of roads.

This microscopic-based research contributed to current state of art through a deep analysis of different jerk classes and thresholds to evaluate global (CO₂) and local (NO_x) pollutant emissions for different driving styles and routes. The use of driving volatility information for recognizing the existence of strong acceleration and aggressive maneuvers in instantaneous driving decisions is well-demonstrated. Thus, the methodology and thresholds used in this paper can be integrated into a framework by means of warning and alerts for drivers to reduce emissions and volatile driving behaviors, and simultaneously to improve road safety. The research methodology can be generalized to other vehicles with different powertrains, sizes or emission standards, as well as drivers with different driving styles.

Due to small sample size of the fleet, number of drivers and routes, more field data are needed. Further experimental investigation on gasoline, hybrid, vans and diesel vehicles, with focus on newer vehicles (Euro 6c and Euro 6d) could be interesting, especially for NO_x due to the increased decoupling of emissions in the more sophisticated and more efficient aftertreatment systems.

One limitation of this study is that it only consisted of light duty vehicles with diesel engines. The second limitation is related to the unobserved heterogeneity of data that was not taken into account.

Future research will be focused on the incorporation of power demand, acceleration and jerk thresholds into a driver decision support algorithm by considering safety and environmental aspects through warning messages. The relationship between driving volatility and following distance, position (using right lane versus left lane) or lateral distance during overtaking would be also explored.

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