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 a 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.

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, 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 (NOx) 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 of 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 (Kilinc & Baybura, 2012; Lårusdottir & 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; Lårusdottir & 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., 2015; Kamrani et al., 2018), 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 (CO₂) and NOx 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

| Route 1 - A1 | Route 2 - A29 | Route 3 - N109 |
|--------------|---------------|---------------|
| Parameter    | c1 | c2 | c3 | c4 | c1 | c2 | c3 | c4 | c1 | c2 | c3 | c4 |
| # of trips   | 2  | 2  | 1  | 2  | 4  | 2  | 2  | 2  | 5  | 4  | 3  | 4  |
| speed (km.h⁻¹) | mean | 123 | 101 | 123 | 114 | 115 | 105 | 109 | 18  | 14 | 19 | 15  |
|              | std | 11  | 7  | 19  | 119 | 13  | 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 |
| 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 |
| NOx (g.km⁻¹) | mean | 4.97 | 2.17 | 2.12 | 2.20 | 2.89 | 2.23 | 4.31 | 1.82 | 1.55 | 2.09 | 0.41 | 1.56 |
|              | 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 |
| CO₂ (g.km⁻¹) | mean | 324 | 170 | 202 | 180 | 263 | 183 | 279 | 174 | 258 | 151 | 146 | 319 |
|              | std | 23  | 4  | 37  | 37  | 45  | 1  | 29  | 2  | 63  | 40  | 1  | 12  |
| fuel (L/100 km) | mean | 12.18 | 6.38 | 7.29 | 6.75 | 9.85 | 6.84 | 10.38 | 6.47 | 8.9  | 5.38 | 4.41 | 6.65 |
|              | 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 (rev.min⁻¹) | mean | 2517 | 2104 | 2286 | 2111 | 2319 | 2191 | 2418 | 2007 | 1595 | 1303 | 1275 | 1369 |
|              | std | 356 | 140 | 356 | 119 | 362 | 262 | 312 | 219 | 362 | 262 | 312 | 219 |

Table 2. Descriptive statistics regarding each vehicle record.

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

| Pair                      | Total |            |            |
|---------------------------|-------|------------|------------|
| NOx-CO₂                   | 94%   | 100%       | 81%        |
| RPM-speed                 | 59%   | 18%        | 63%        |
| Fuel consumption-CO₂      | 71%   | 27%        | 41%        |
| Fuel consumption-NOx      | 18%   | 18%        | 5%         |
| Fuel consumption-acceleration | 47%  | 18%     | 9%         |
| RPM-NOx                   | 6%    | 2%         | 0%         |
| Altitude-Nox              | 6%    | 0%         | 5%         |

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and acceleration thresholds with those based on RPA, MPA, and power demand; and (2) to assess the influence of vehicular jerk on trip-specific CO₂ and NOₓ 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 on-road assessments with those based on RPA, MPA, and acceleration thresholds with those based on RPA, MPA, and power demand; and (2) to assess the influence of vehicular jerk on trip-specific CO₂ and NOₓ emissions.

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.

All measurements were carried out in fall 2018 in four different light duty diesel vehicles (c1–c4) with four different drivers (three males and one female, ages between 30 and 40 years old) to capture different driving styles. It must be noted that each driver drove always the same vehicle. The probe vehicles were equipped with a portable emission measurement system (PEMS), on-board diagnostic readers (OBD), and a Global Navigation Satellite System (GPS) data logger, and driven along with the traffic stream by different persons for different driver behaviors. The testing vehicles vary in category, emissions standards, engine displacements, and mileage, as presented in Table 1. All vehicles have a five-gear manual transmission. Total data include 33 trips and approximately 26 000 sec of valid PEMS, OBD, and GPS data. For this research, the database consisted of 20 571 sec from 33 trips with a road coverage of approximately 355 km. Descriptive statistics are presented in Table 2, by vehicles and route. More details about the studied routes, experimental design, instruments and test conditions, field measurements and emission calculations can be found elsewhere (Fernandes et al., 2019b).

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, NOₓ, 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 NOₓ and CO₂. As expected, fuel consumption is strong correlated with CO₂ in more than 70% of samples on motorways but not with NOₓ, which is in concordance with previous literature (Fontaras et al., 2017). The amount of CO₂ emissions and fuel consumption depends on several parameters such as type of vehicle, driving behavior, road, and engine characteristics. NOₓ emissions in diesel vehicles depend not only on engine load and engine revolution, but also on the exhaust after-treatment system, such as Lean NOₓ Trap and Selective Catalytic Reduction (Giechaskiel et al., 2014; Johnson, 2016; Bai et al., 2017). These after-treatment systems have been contributing to less emission amounts in recent vehicles, thereby explaining the high NOₓ-fuel relation in Euro 4 (~18%) compared to Euro 6b (~5%). In contrast, RPM and Altitude show a strong correlation in only 6% and 3% of motorway and all route trips, respectively.

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, NOₓ, RPM, fuel consumption, and altitude can be found elsewhere (Fernandes et al., 2019b).

**Table 4. Linear regression between speed with: CO₂, NOₓ, VSP mode, RPM, fuel consumption, and altitude.**

| ID | Model | p-value | Adjusted R² |
|----|-------|---------|-------------|
| Route | A1 | y = 39.269 + 0.9397 x₁ + 0.7169 x₃ + 0.0329 x₄ - 0.4129 x₅ - 0.5544 x₆ | 0.637 |
| A29 | y = 33.104 + 1.4146 x₁ + 20.4580 x₂ + 0.0804 x₃ + 0.0322 x₄ - 0.6250 x₅ | 0.720 |
| N109 | y = 2.2943 + 99.3040 x₂ + 0.0115 x₃ + 0.0310 x₄ - 0.3235 x₅ - 0.0910 x₆ | 0.505 |
| Driver | c₁ | y = -23.9650 + 1.2696 x₁ + 0.1189 x₃ + 0.0485 x₄ - 0.5044 x₅ - 0.2121 x₆ | 0.826 |
| c₂ | y = -5.2520 + 2.3621 x₁ + 32.3180 x₂ + 0.0459 x₃ - 0.5736 x₄ + 0.2506 x₅ | 0.912 |
| c₃ | y = -11.2970 + 4.2241 x₁ + 47.4110 x₂ + 0.0261 x₃ + 0.0349 x₄ - 0.3238 x₅ + 0.3482 x₆ | 0.832 |
| c₄ | y = -11.2970 + 4.2241 x₁ + 47.4110 x₂ + 0.0261 x₃ + 0.0349 x₄ - 0.3238 x₅ + 0.3482 x₆ | 0.832 |

Note: x₁ represents CO₂, x₂ represents NOₓ, x₃ represents a VSP mode, x₄ represents RPM, x₅ represents fuel consumption, and x₆ represents the altitude.
Figure 3. Scatter plot of instantaneous speed together: (a) CO₂, (b) NOₓ, (c) Fuel consumption, (d) RPM, and (e) altitude for Route A29.
adjusted \( R^2 \) 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–S5.

The relationships between five driving behaviors (from ten identified) are analyzed using the scatter plot of A29 in Figure 3a–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-NOx 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 NOx can identify five different driving behaviors. Figure 3d–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 NOx emissions per unit distance for motorways, where is possible to identify four different driving behaviors (Figure 4a,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.

2.2.3. Principal component analysis

PCA is a statistical multivariate technique that allows to reduce the original set of variables \( (X_1, X_2, \ldots, X_p) \), in a
Figure 4. Scatter plot for vehicle c2 of instantaneous speed together: (a) CO\textsubscript{2}, (b) NO\textsubscript{x}, (c) Fuel consumption, (d) RPM, and (e) altitude.
smaller set of non-correlated variables called principal components PCs ($Y_1, Y_2, \ldots, Y_p$), 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 $X$ 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 & Wichern, 2007).

Let $X_1$ as speed, $X_2$ as jerk, $X_3$ as CO$_2$, $X_4$ as NOx, $X_5$ 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.

The reduced models with only the first two components are described in Table 6. The construction of the principal

| 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 |

Note: Values represent the percentage of variability.
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 \( X_8 \) (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.

| Route | Driver | ID | model |
|-------|--------|----|-------|
| Route A1 Y 1 | c1 | \( Y_1 = 0.0359 \times x_1 + 0.0080 \times x_2 + 0.0002 \times x_4 + 0.0022 \times x_5 + 0.9992 \times x_6 + 0.0080 \times x_7 + 0.0148 \times x_8 \) |
| Route A29 Y 1 | c2 | \( Y_2 = -0.0509 \times x_1 + 0.0001 \times x_2 + 0.0216 \times x_3 + 0.0008 \times x_4 + 0.0155 \times x_5 - 0.0132 \times x_6 + 0.0135 \times x_7 + 0.9992 \times x_8 \) |
| N109 Y 1 | c3 | \( Y_3 = 0.0429 \times x_1 + 0.0080 \times x_2 + 0.0002 \times x_4 + 0.0030 \times x_5 + 0.9990 \times x_6 + 0.0072 \times x_7 - 0.0024 \times x_8 \) |
| A29 Y 1 | c4 | \( Y_4 = 0.1336 \times x_1 + 0.0331 \times x_2 + 0.0007 \times x_4 - 0.0048 \times x_5 + 0.0036 \times x_6 + 0.0259 \times x_7 + 0.9893 \times x_8 \) |

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.
Since the focus of this article 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, CO$_2$, NOx, Vehicle Specific Power – VSP (Frey et al., 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 et al., 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.

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

### 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 | 0.0000  |
| CO$_2$                 | 0.0000| 0.0000 | 0.0000  | 0.0000| 0.0000 | 0.0000  |
| NOx                    | 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.

### Table 8. Parameters thresholds of the driving style.

| Parameter                     | Reference                    | Values | Notes               |
|-------------------------------|------------------------------|--------|---------------------|
| jerk (m.s$^{-3}$)             | Kilinc and Baybura (2012)    | 0.9    | –                   |
| maximum acceleration (m.s$^{-2}$) | Choi and Kim (2017)          | 1.47   | motorways           |
| maximum deceleration (m.s$^{-2}$) | Deligianni et al. (2017)   | 3.4    | urban and rural     |
| Time speed limit exceed more than 10 sec | BÃrgman 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               |
| RPA (m.s$^{-2}$)              | (Grunditz, 2014)             | 0.3    | Rural               |

2.2.4. ANOVA

Since the focus of this article 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, CO$_2$, NOx, Vehicle Specific Power – VSP (Frey et al., 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.
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 CO$_2$ emissions. In a research conducted by Bargman 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 sec.” In this study, the proposed driving style classification is constructed based on several thresholds presented in Table 8. The

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.
Figure 8. Mass power frequency by route: (a) A1; (b) A29; and (c) N109.
Figure 9. Accumulated CO₂ (g/km) by power demand and route: (a) A1; (b) A29; and (c) N109.
Figure 10. Accumulated NOx (g/km) by power demand and route: (a) A1; (b) A29; and (c) N109.
definitions of the driving behavior are the same as Gallus et al. (2017) work, that is, aggressive, normal severe, and calm.

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

As mentioned before, RPA (Gallus et al., 2017), MPA (Gallus et al., 2017; Fernandes et al., 2019b), 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 Eq. (1) (EC, 2016):

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

(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 Eqs. (2) and (3), respectively:

$$RPA = \frac{\sum_i \frac{v_i}{5.8} a_i^+}{d}$$

(2)

$$MPA = \text{average}(a_i^+)$$

(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 New European Driving Cycle (NEDC), but research team uses the set point of 21.01 m$^2$.s$^{-3}$ according to the Worldwide harmonized Light duty driving Test Cycle (WLTC). It must be emphasized that the 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).

From Figure 9, it can be noted that strong positive power demand was associated with highest amount of CO$_2$ 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 CO$_2$ values 2.5 times higher in strong positive than the other classes while c2 and c3 obtained the highest CO$_2$ values in strong positive (more than 10% higher the average values) and mild positive classes (12% higher than the average values), respectively.

All vehicles recorded the highest amount of NOx emissions per unit distance in strong positive class along A1, as exhibited in Figure 10. This class had on average an accumulated NOx between 24% and 46% for c3 and c1, respectively, higher than the average values of other classes. The

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

| Route | Vehicle | CO$_2$ (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              |

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

### 3. Results

#### 3.1. RPA and MPA

Figure 8a–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 7e 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.

#### 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).

From Figure 9, it can be noted that strong positive power demand was associated with highest amount of CO$_2$ 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 CO$_2$ values 2.5 times higher in strong positive than the other classes while c2 and c3 obtained the highest CO$_2$ values in strong positive (more than 10% higher the average values) and mild positive classes (12% higher than the average values), respectively.
Figure 11. Jerk range frequency by route: (a) A1; (b) A29; and (c) N109.
Figure 12. Accumulated CO₂ (g/km) by jerk range frequency and by route: (a) A1; (b) A29; and (c) N109.
Figure 13. Accumulated NOx (g/km) by jerk range frequency and by route: (a) A1; (b) A29; and (c) N109.
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 NOx increased up to 1.5 g.km\(^{-1}\), but c3 and c4 achieved similar NOx values among classes of power demand. This happens because almost all vehicles were not subjected to maximum power demand along route.

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 CO\(_2\) and NOx emission results using the threshold of 21.01 m\(^2\).s\(^{-3}\) and the threshold value of m\(^2\).s\(^{-3}\) proposed by Frey et al. (2002) by vehicle and route. The resulting emissions per unit distance were equal in both strategies 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 (4–9%, 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.

### 3.3. Vehicular jerk

Figure 11a–c displays the percent of time spent in each jerk class in 0.5 m.s\(^{-1}\) 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\(^{-1}\) to 4 m.s\(^{-1}\)) than highway routes (Figure 7c). This was due to the fact that drivers were continuously pressing 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.

The higher accumulated CO\(_2\) emissions per unit distance in highways were generated in extreme jerk classes, as exhibited in Figure 12a,b. For example, c1 accumulated CO\(_2\) per unit distance in jerk classes of −1.5 m.s\(^{-1}\) and 1.0 m.s\(^{-1}\) was two times higher than the accumulated values achieved in other classes. In contrast, almost all vehicles yielded the lowest accumulated CO\(_2\) per unit distance in jerk class of 0 m.s\(^{-1}\) in both motorway routes. The distribution of jerk versus CO\(_2\) varied among drivers; the difference between extreme A29-CO\(_2\) accumulated values was much lower in c2 than 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 CO\(_2\) by jerk class was dissimilar regarding to prior routes, as depicted in Figure 12c. All vehicles produced the higher level of CO\(_2\) in jerk classes higher than the threshold value of 0.9 m.s\(^{-1}\) (0–80% higher than the average CO\(_2\) trip, depending on vehicle). For jerk classes between −1.5 and 1.0 m.s\(^{-1}\), the resulting accumulated CO\(_2\) little varied for the same driver.

Figure 13a–c shows the distribution of NOx values per unit distance and jerk class by route type. Main results suggested similar jerk distributions to CO\(_2\) values, which is expected since the analysis of CO\(_2\) and NOx showed positive correlation between these variables. Almost all vehicles produced the highest level of accumulated NOx in extreme positive jerk classes (> 1 m.s\(^{-1}\)) (0–25% higher than the average trip value, depending on the vehicle and route). The values near zero jerk had the lowest accumulated NOx values, regardless of the vehicle. For jerk classes between −1.5 and 1.0 m.s\(^{-1}\), the range of NOx values was not high, especially in N109.

The analysis of Figures 12 and 13 seems to confirm from an increasing trend from negative to null jerk values in CO\(_2\) and NOx in several trips. Thus, driving volatility could have an important effect on emission levels. According to Wang et al. (2015) and Kamran 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 CO\(_2\) and NOx emission values per unit distance were computed for negative jerk values with positive acceleration values in the previous 4 sec,\(^{1}\) as listed in Table 10. Although the results are only displayed for c1, other vehicles recorded identical values among jerk time series. Both CO\(_2\) and NOx were much higher than values obtained in zero jerk values (on average 7–18% higher than CO\(_2\) and NOx 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.

Figures 14–16 plot CO\(_2\) and NOx emission rates, and vehicular jerk and acceleration over the time for the most volatile driver (c1). The horizontal solid line represents the

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There 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.
Figure 14. Jerk and acceleration profiles versus emissions for driver 1 in A1: (a) acceleration versus CO₂; (b) jerk versus CO₂; (c) acceleration versus NOx; and (d) jerk versus NOx.
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$^{-3}$, CO$_2$ and NOx 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 sec) 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 sec, which represented just 3% of trip time (see Figure 16). The CO₂ and NOx 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 NOx than for CO₂. The analysis of other vehicles resulted in similar conclusions to c1.

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 LDVs, 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 NOx emissions, regardless of the route type.

The comparison of jerk classes and emissions per unit distance indicated that the accumulated CO₂ and NOx 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 (NOx) 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 article 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 NOx due to the increased decoupling of emissions in the more sophisticated and more efficient after treatment systems.

One limitation of this study is that it only consisted of LDVs 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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