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Biplots of kinematic variables and pollutant emissions for an intercity corridor

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Abstract

A thorough understanding of driver behavior is an important step to improve the environmental performance of road traffic. Accurate data analysis tools can be valuable to identify these concerns. The present study explores relationships between driving patterns, tailpipe emissions, and road differentiation by using Principal Component Analysis Biplot. This statistical methodology is suitable to identify patterns hidden in data and can be used as a visualization tool. In this study, the key variables included were: speed, engine speed (RPM), acceleration, and vehicular jerk (first derivative of acceleration), as kinematic variables, and carbon dioxide (CO_2), nitrogen oxides (NOx), and VSP (Vehicle Specific Power) mode, as pollutant emission variables. For this purpose, second-by-second vehicle dynamics and tailpipe emissions data were collected in three passenger cars with different powertrains (gasoline, diesel, and hybrid) along with different types of routes (one partly urban/rural and two motorways with variations in traffic volumes) in Aveiro Region (Portugal). Results revealed that Biplots allowed to distinguish different driving behaviors, separate route types (urban/rural from motorways), establish some remarks about emissions, and also present the correlated variables in a single plot. Therefore, this technique can be considered as a useful visualization tool to explore real traffic-related data.

Keywords: Biplots; Principal Component Analysis; tailpipe emissions; kinematic variables

1. Introduction and Research Objectives

Road transport represented more than 21% of transport-related Greenhouse Gas emissions in 2018, and being also responsible for approximately 39% and 11% of the total nitrogen oxides (NOx) and primary particulate matter with a diameter of 2.5 μm or less ($PM_{2.5}$) emissions, respectively (EEA (2019), EEA (2020)).
There is no extensive literature regarding the application of Principal Component Analysis (PCA) in driving and/or

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tailpipe emissions. In Prati et al. (2011), PCA was applied to analyze different driving cycles on the chassis dynamometer of Euro 3 motorcycles measuring exhaust emissions and fuel consumption. Chen et al. (2018) have established an eco-driving behavior model using fuel consumption, engine speed, speed, engine torque, and also GPS coordinates through PCA and linear regression. Using PCA, mutual information, and Spearman correlation, Prieto et al. (2010) concluded that using an inertial sensor to obtain frontal inclination and engine revolutions per minute (RPM) are relevant to estimate the driver activity on brake and throttle pedals. PCA was also used to obtain driving style classification in Liu et al. (2019) and Escaño et al. (2020). Pan et al. (2020) used PCA technique to construct a driving cycle strategy. Moreover, a combination of PCA and data mining techniques was applied to represent an urban driving cycle for electric vehicles in Zhao et al. (2020).

Emission factors of different diesel fuel types of buses were investigated using PCA in Lim et al. (2007). Trends of atmospheric emissions produced by the road transport sector in Italy between 1990 and 2016 were investigated in Iarocci et al. (2019). Using PCA, groups of pollutants with similar behavior were identified. Emission factors of heavy-duty and light-duty vehicles from a air pollution road-side unit in Los Angeles were studied in Kelp et al. (2020). They identified a ratio cutoff separating regular and high-emitting vehicles.

Recently, Ferreira et al. (2021) applied PCA as an exploratory analysis regarding emissions and kinematics variables. They verified that different driving behavior could be identified from calm to aggressive, but the study only considered vehicles powered by diesel engines.

The literature review revealed that the use of visualization tools for data analysis is quite scarce, in particular in what concerns vehicle data record and its relationship with exhaust emissions through visualization analysis that exhibits point cloud and variables at the same time. The aim of this research is to use PCA Biplot (originally developed by Gabriel (1971)), as a powerful visualization tool for explanatory data analysis that can be applied to identify differences between vehicles regarding emissions. It is hypothesized that the PCA Biplot technique enables correlations between emissions and kinematic variables, distinguishes road types and driving profiles. Therefore, three different engine vehicles (hybrid, diesel, and gasoline) with European Emission Standard 6c are considered and three different routes of an intercity corridor are studied (one partly urban/rural and two motorways). PCA Biplots are applied to three different routes and each vehicle concerning different sets of variables: i) all variables; ii) emission variables (carbon dioxide (CO_2), NOx and VSP (Vehicle Specific Power) mode); and iii) kinematic variables (speed, RPM, acceleration, and vehicular jerk).

The novelty of this work relies on the application of PCA Biplots as a visualization tool for exploring patterns within the vehicle performance data under real driving emissions driving conditions.

2. Methodology

2.1. Data Collection

Field measurements were collected in Aveiro Region (Portugal), along one urban/rural (N109) and two motorways (A1 and A29) routes in both directions of travel. A1 and A29 have different traffic volumes (see Fernandes et al. (2019b)), road grades, and tolling systems, while N109 is a national road partly conducted on a rural (63%) and urban (37%) road. The three passenger cars were equipped with an Integrated Portable Emission Measurement System (iPEMS), on-board diagnostic readers (OBD-II), and a Global Navigation Satellite System (GPS) data-logger were driven along with the traffic stream by three different persons (ages between 20-40 year old) to account for different driver behaviors. From iPEMS, volumetric fractions of CO_2, NOx were measured, while OBD-II allows obtaining several kinematic variables such as speed, engine RPM acceleration, and vehicular jerk. All data were measured/recorded on a second-by-second basis. The testing vehicles vary in the category, engine displacements, and mileage, as presented in Table 1.

In this study, total data include 17 trips with a road coverage of approximately 230 km and 12 150 seconds. More details about data processing and quality assurance, experimental design, studied routes, instruments and test conditions, field measurements and emission calculations can be found in Fernandes et al. (2019a) and Fernandes et al. (2021). The data set included three vehicles with European emission standard 6c. PCA biplots were constructed for each route (N109, A29, and A1) and each vehicle (V1-V3) considering: a) all variables; b) only emission variables; and c) only kinematic variables.

Table 1: Technical specifications of the tested vehicles.

Vehicle	Engine	Year	European Emission Standard	Mileage (km)	Engine Displacement (cm^3)	Horse Power (hp)
V1	Hybrid Electric	2019	EURO 6c	7500	1800	122
V2	Diesel	2019	EURO 6c	5600	1248	65
V3	Gasoline	2019	EURO 6c	2500	1000	100

2.2. Principal Component Analysis

PCA is a statistical multivariate technique that transforms the original set of variables $(x_1, \ldots, x_P)$, into a partition of uncorrelated variables called principal components PCs $(y_1, \ldots, y_P)$, that are ordered so that the first few PCs retain most of the variation present in all of the original variables , which is the reason why PCA is often associated to a dimensionality reduction technique (Jolliffe (2002)). Each PC is a linear combination of all 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, meaning that redundant information is not found. More details about PCA are explained here Jolliffe (2002).

2.3. Biplots construction and analysis

Biplot construction is obtained as follows: let $\mathbf{X}$ be the data matrix with the n observations measured on p variables. The Singular Value Decomposition of $\mathbf{X}$ is defined as $\mathbf{U\Sigma V}^{\mathrm{T}}$, where $\mathbf{U}$ is a matrix whose columns vectors are orthonormal and corresponds to the eigenvectors of $\mathbf{XX}^{\mathrm{T}}$; $\mathbf{V}$ is a matrix whose column vectors are also orthonormal and corresponds to the eigenvectors of $\mathbf{X}^{\mathrm{T}}\mathbf{X}$, and $\mathbf{\Sigma}$ is a diagonal matrix containing the singular values arranged in decreasing order Tejedor-Flores et al. (2017). Therefore, for the GH-Biplot, $\mathbf{U\Sigma}$ corresponds to scores of observations through PCA and $\mathbf{V}^{\mathrm{T}}$ to the obtained coefficients by PCA. After the representation displayed, it can be interpreted as Nieto et al. (2014):

- the distance between each pair of two points is considered as a dissimilarity measure and corresponds to the (dis)similarity between the associate observations;
- the arrow length represents the variable variance. The cosine of the angle between the vectors approximates the correlation between the variables that they represent. Moreover, biplots can be used to detect clusters, such as the group formed by very similar observations;
- the relationships between observations and variables can be understood through the projections of the points onto the arrows;
- the measure of the relationship between the axis of biplots and each of the observed variables represents the variability proportion of each variable explained by the factor, which enables knowing which variables are more related to each axis.

2.4. Vehicle Specific Power methodology

The microscopic VSP methodology (USEPA (2002)) is a function of speed, acceleration-deceleration and slope, as shown in Eq.1

$$VSP = v\,[1.1a + 9.81\sin(\arctan(grade)) + 0.132] + 0.000302v^3 \qquad (\mathrm{kW/ton}), \tag{1}$$

where v is the instantaneous speed (m/s); a represents the instantaneous acceleration/deceleration (m/s^2), and *grade* is the road slope (in decimal fraction). VSP is a representative variable of the traction power and these values can be assigned to 14 modes/bins for light-duty vehicles (USEPA (2002)), which in turn are associated to specific emission rates. Usually, modes 1 and 2 are associated with negative power ranges associated with braking or with negative slope. Mode 3 represents idling (when the vehicle is stopped) and low speed situations, while VSP modes from 4 to 14 are associated cruising, acceleration, or uphill driving.

2.5. Global Sensitivity Analysis

Sensitivity analysis allows identifying the parameters for which a small variation implies a large variation in model output. These parameters can be called sensitivity parameters. Global sensitivity analysis was constructed through the probability distribution of the output to define sensitivity indices, defined as Sobol indices (Saltelli et al. (2008)). The sensitivity of an output to an input variable is therefore the fraction of the variation in the output that can be explained by the variation in the input variable, either alone (i.e., the main effect), or in conjunction with other variable inputs (i.e., total effect). After that, the input variables are sorted in terms of global sensitivity indices (GSI) measures (Saltelli et al. (2010)).

3. Results

ANOVA was carried out to check if there exist significant differences within each route between the different vehicles to decide about the inclusion of the VSP mode variable. Significant differences between routes were found at a 95% confidence level (p-value<0.01). Furthermore, using multiple comparisons leads to conclude that vehicle V3 is significantly different from all other vehicles for all routes. This is mainly due to an aggressive pattern of very high speeds on motorways; the percentage of time at speeds above 135 km/h was 1%, 11% and 14% in V1, V2 and V3, respectively. Moreover, VSP modes are shown to be correlated with fuel consumption, CO_2 and NOx emission factors (Frey et al. (2006), Coelho et al. (2009)). Aiming to understand which variables (speed, RPM, acceleration, vehicular jerk, CO_2, NOx, VSP mode) can identify hidden patterns on data and distinguish vehicles/drivers, the following case study was considered regarding emission variables: European Emission Standard 6c vehicles with different engine types. Finally, a sensitivity analysis using Sobol indices was performed on kinematics variables to evaluate their influence on emissions variables.

Table 2: Summary of explained variance (%) using the first two principal components: i) only kinematic variables; ii) for all variables and only emission variables without VSP mode; iii) for all variables and only emission variables with VSP mode.

Type of analysis		N109	A29	A1	V1	V2	V3
	kinematics	73	81	83	83	86	85
	all variables	60	68	71	72	81	69
	emissions	100	100	100	100	100	100
including VSP mode	all variables	61	66	71	70	78	71
	emissions	84	86	91	89	96	91

Table 2 represents the summary of explained variability by retaining the first two principal components considering the three different types of studies: for all variables, emission variables, and kinematic variables. It can be observed that the largest explained variance is found for route A1 and vehicle V2. Moreover, the maximum variability is reached when variables are separated, regardless of the vehicle and route. It was decided to include the VSP mode in the set of emission variables, since high VSP modes are associated to high speed and acceleration values, making it possible to link emissions to driving behavior. Comparing the values of variance explained by retaining only the first two main components (Table 2), a slight decrease has been found.

For all routes (Figs. 1a, 1c, 1e), there is a clear separation between speed and RPM variables, and vehicular jerk and acceleration variables. This trend can be noted for all biplots (regardless routes and vehicles) with only kinematics variables. Therefore, only biplots with all variables are displayed to understand the relationship between kinematics and emission variables. It seems that CO_2 and RPM, and speed and NOx have a strong correlation (small angle between vectors). For instance, the vectors of speed and NOx are collinear in A1.

For the national road N109, several behaviors can be distinguished (Fig. 1a, and 1b): i) V1 with higher negative vehicular jerk values (greater concentration of points in the third quadrant) and lower CO_2 emissions (which is expected since V1 operates with electric motor in various sections of this route); ii) V2 achieved the highest NOx (because it is powered by a diesel engine) and speed values. The same pattern is observed on motorways (Fig. 1c to 1e), where V2 exhibited wider speed range compared to V1 and V3. These results can suggest aggressive driving behaviors in V2 trips. It was also found that PC1 is mostly explained by CO_2 and RPM on motorways. A close view to the N109 data allowed to see many data points associated to negative vehicular jerk, which is possibly due to the existing singularities along national road, such as intersections, traffic lights, and roundabouts, which can induce constant pedal pressure. For all routes, V1 had a higher point cloud dispersion while V2 and V3 show higher variability in what respects to the emissions, vehicular jerk, and acceleration values. From Figs 1c and 1e, and as suspected, the variability of speed values is larger for trips on A29 and A1. Clusters of high VSP bins (here represented by ellipses in blue color) were also observed in V2 and V3 data sets, as shown in Figs. 1d and 1f. Noted that the percentage of time spent in VSP modes higher than 12 in V2 and V3 was higher than 20% in both motorways.

The analysis of individual vehicles in Figs. 2a, 2c, and 2e allow to differentiate national road from motorways data. CP1 was better explained by the RPM-CO_2 pair for both motorway A29 and national road N109. Concerning A1, NOx is almost collinear with the CP1 axis. The analysis of V1 and V3 showed NOx variable exhibiting less variability (shorter length vector) since these vehicles are powered by a gasoline engine. Another study was conducted including the VSP mode in the emissions analysis, as depicted in Fig. 2b, 2d, and 2f. The results confirmed the correlation between the CO_2-VSP mode pairs for V1 and V3. In the case of V2, there exists a better correlation in CO_2-NOx pair than V1 and V3 do. This is mostly due to the fact that V1 and V3 are powered by gasoline engines, thus presenting low NOx values that in many cases are below the detection limit of the instrument (Fernandes et al. (2021)). V1 emissions exhibited a greater dispersion along A29 where high VSP modes were more predominant than in the other roads (red points in the first quadrant of Fig. 2d), perhaps due to a greater percentage of strong downhill and strong uphill in A29 (Ferreira et al. (2021)). Despite the result, V1 presented a higher frequency of low VSP modes (concentration of the orange point cloud), which may suggest calm driving. V3 yielded a higher frequency of aggressive VSP modes in A1, as indicated by points projected orthogonally on the VSP mode vector in Fig. 2f. The variability emissions (points projected orthogonally on NOx and CO_2 vectors) is found to be lower on A29 compared to A1 (there are more orange points distributed in the first quadrant) which is due to the higher traffic volumes in A1 (Fernandes et al. (2019b)) resulting in more overtaking maneuvers and variation in acceleration values.

A global sensitivity analysis quantifies the contribution of the variances of the set of input parameters, here, kinematic plus engine RPM to output variance (emissions). Indeed, a sensitivity index describes how much each input variable leads to the output variance. Using the multisensi R library, first, a dimension reduction is applied (PCA) then sensitivity analysis is performed to the associated coefficient of the decomposition (Lamboni et al. (2011)). According to the sensitivity indices classification provided by Cannavó (2012), only RPM can be considered as very important to explain emissions in all studied cases. For instance, results of GSI considering motorway A1 and vehicle V1 are displayed in Fig. 3. The strong correlation between RPM-CO_2 was exhibited in all biplots, therefore, this result reinforces the applicability of PCA biplot.

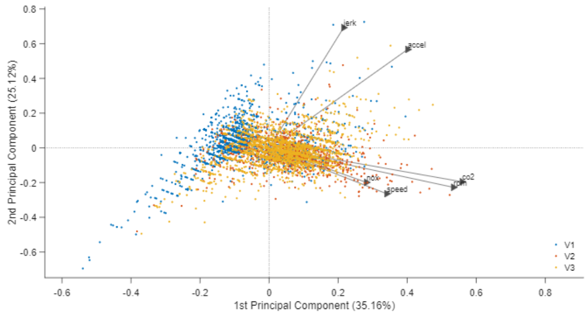
4. Conclusions

The relationship between driving patterns, tailpipe emissions, and road types using a PCA Biplot was identified. Data were collected from three vehicles with different propulsion technologies (gasoline, diesel, and hybrid). Although the variability of all data stand was explained in the range 60-100%, PCA biplots showed as a useful visualization tool in the identification of aggressive driving behaviors, differentiation between motorways from national roads trips, and correlation of kinematic and emission variables. Results indicated that the inclusion of the VSP modes variable in the PCA decreased the explained variability in the data set, but it allowed to visualize vehicles with aggressive driving behavior based on their tailpipe emissions. PCA also identifies the variability in vehicular jerk (an indicator of driving volatility) in routes containing different traffic control treatments, as well as the variability in acceleration and emissions values for motorways routes exhibiting different traffic volumes. This technique could detect a correlation between CO_2 and engine speed in all routes and vehicles.

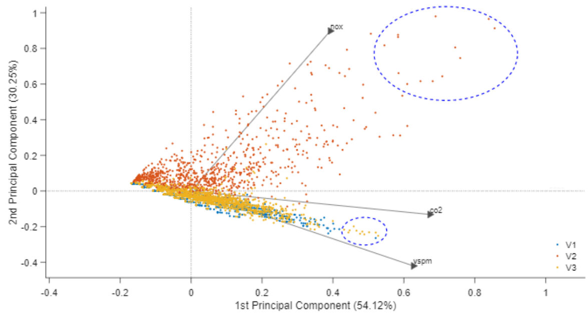
The major contribution of the research is that it uses an effective visualization tool capable of recognizing driving profiles in different types of roads, regardless of the vehicle powertrain. Therefore, the proposed methodology can be used to explore other vehicle types with different emissions standards, which include, for instance, the upcoming Euro 7 emission regulations.

This research presents some limitations: 1) data from three vehicles only were examined; 2) V2-V3 datasets revealed some outliers in what concerns the high-speed values (above 135 km/h) on motorways, which may pose some bias in the obtained results.

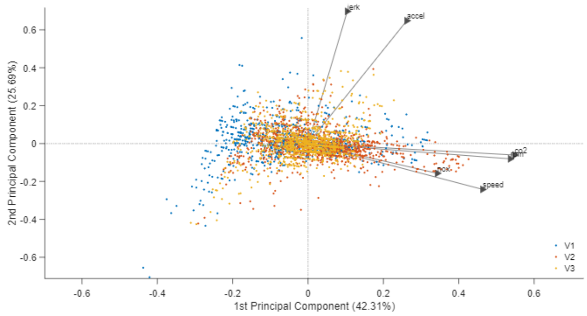
In this work, the classical biplot representation called GH-Biplot was used to provide a high-quality representation of the observations. Future work would include the use of clustering disjoint HJ-Biplot to find the best classification of the observations without penalizing the classification of the variables in a reduced space. Considering the main goal of the manuscript, a comparison between the different biplot methods will be addressed and Factor Analysis will be carried out as a complementary technique to PCA. Additionally, no comparison of conventional statistical to learning methods is provided. Nevertheless, forthcoming work will address this and present a comparison of different classifiers performance. Ongoing work is focused on providing a thorough analysis on the correlation in space and time for each driving behavior.



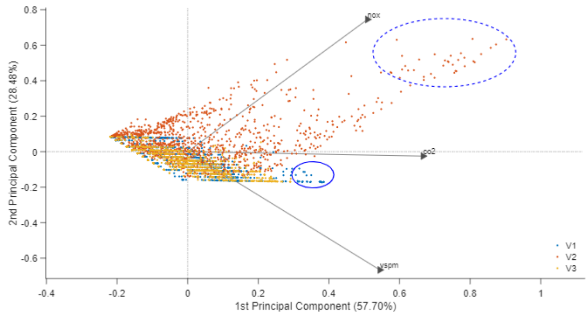
(a) National road N109 without VSP mode.



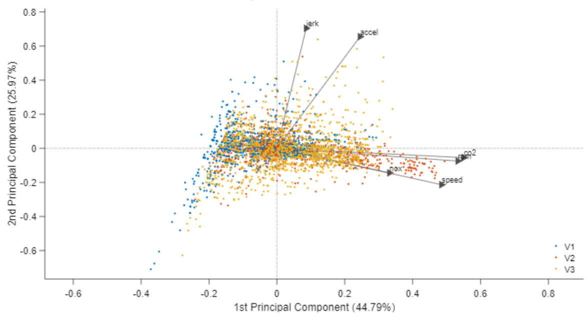
(b) National road N109 with VSP mode.



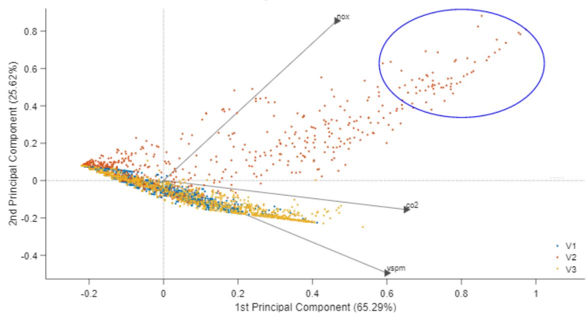
(c) Motorway A29 without VSP mode.



(d) Motorway A29 with VSP mode.



(e) Motorway A1 without VSP mode.



(f) Motorway A1 with VSP mode.

Fig. 1: Biplots for all variables without VSP mode (left side) and emission variables with VSP mode (right side) for all routes regarding vehicles with European Emission Standard 6c.

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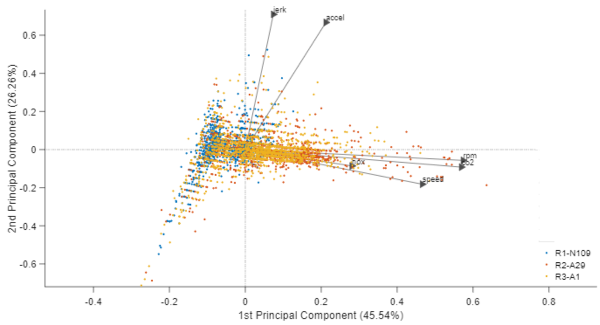
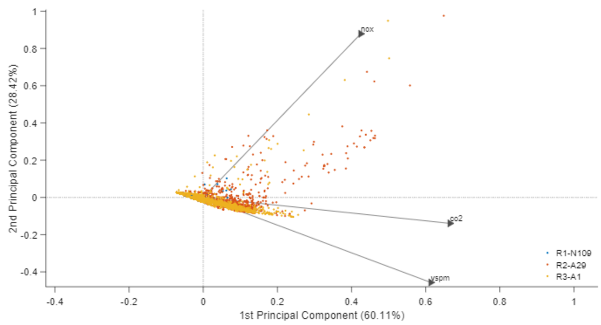
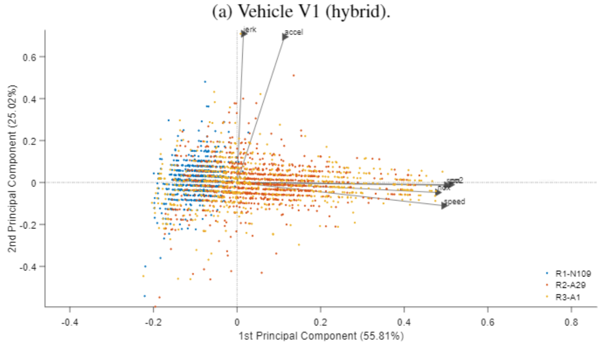


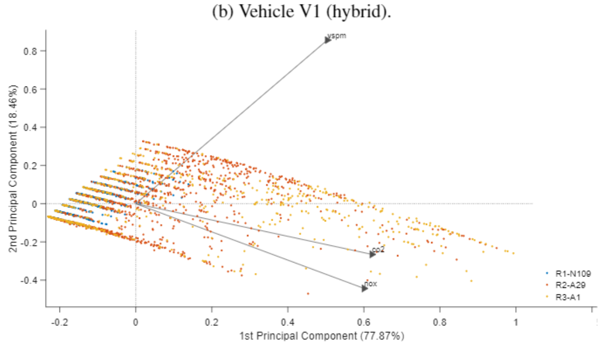
(a) Vehicle V1 (hybrid).



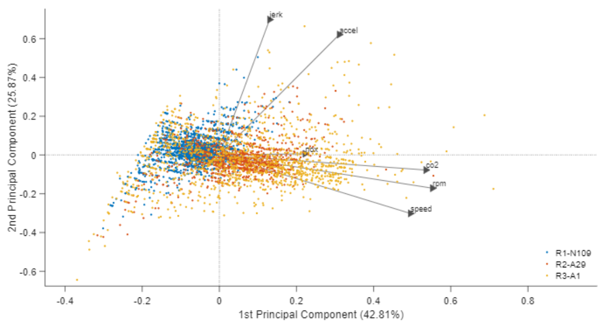
(b) Vehicle V1 (hybrid).



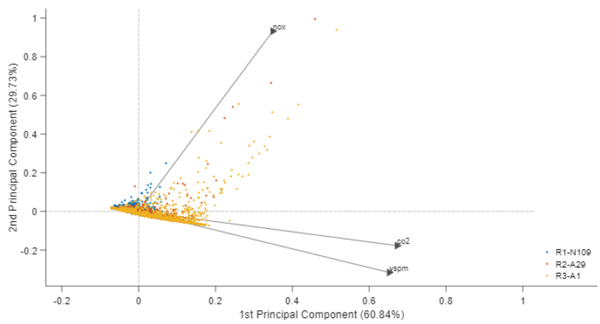
(c) Vehicle V2 (diesel).



(d) Vehicle V2 (diesel).

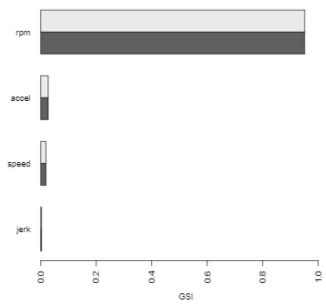


(e) All variables for Vehicle V3 (gasoline).

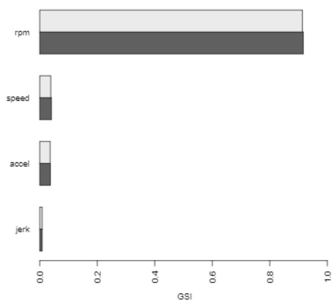


(f) Emission variables for Vehicle V3 (gasoline).

Fig. 2: Biplot for all variables without VSP mode (left side) and emission variables including VSP mode (right side) for all routes regarding vehicles with European Emission Standard 6c.



(a)



(b)

Fig. 3: GSI for: (a) route A1 and (b) vehicle V1. The pale bars corresponds to the average main effects and the dark bars to the total effects.

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