

An Overview of Safety and Emissions Algorithms for the Interaction with Vulnerable Road Users

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Abstract

Road traffic is responsible for several deaths, injuries and high levels of pollutant emissions. There exist studies on safety or emissions issues, but **there is a lack of an integrated approach considering safety-emission hotspots, namely, with respect to impacts involving Vulnerable Road Users (VRU) - pedestrians and cyclists.** In addition, there will be a transition phase where conventional vehicles and CAV will coexist and share the road infrastructure. Therefore, this Ph.D. research seeks to develop integrated research focused on advanced algorithms to reduce driving behavior volatility through safety warnings and emissions in an urban environment focusing on the transition phase.

Ph.D. research goals

The research questions that this Ph.D. will address are:

- Which strategies are adopted by each driver while performing short-term driving decisions and how can these intentions be mapped, for a certain road network?
- How is driver's volatility affected by the proximity of other road users, namely VRU?
- How to predict driver's decision through driving variability in urban context?
- How to integrate inadequate driving behavior in terms of volatility into a platform to inform drivers about potential road hazard warnings on possible upcoming events?
- How can anomalous driving variability be reduced in autonomous vehicles, in order to prevent road accidents and at the same time optimize their performance with a minimum degree of emissions?

Methods

In order to answer the previous questions, the following methodologies are considered:

- Acquisition of real data driving;
- Acquisition of driving simulator data;
- Optimization methods to evaluate driving behavior.
- Markov Decision Process to support driver's decision.
- Statistical and Data Mining methods to analyze of the effect of the presence of other road users in modifying driver decisions.
- Estimation of safety and emission impacts.

References

[1] Fernandes, P., Macedo, E., Bahmankhah, B., Tomás, R., Bandeira, J. M., & Coelho, M. C. (2019). *Are internally observable vehicle data good predictors of vehicle emissions?* Transportation Research Part-D: Transport and Environment, 77, 252-270. <https://doi.org/10.1016/j.trd.2019.11.004>

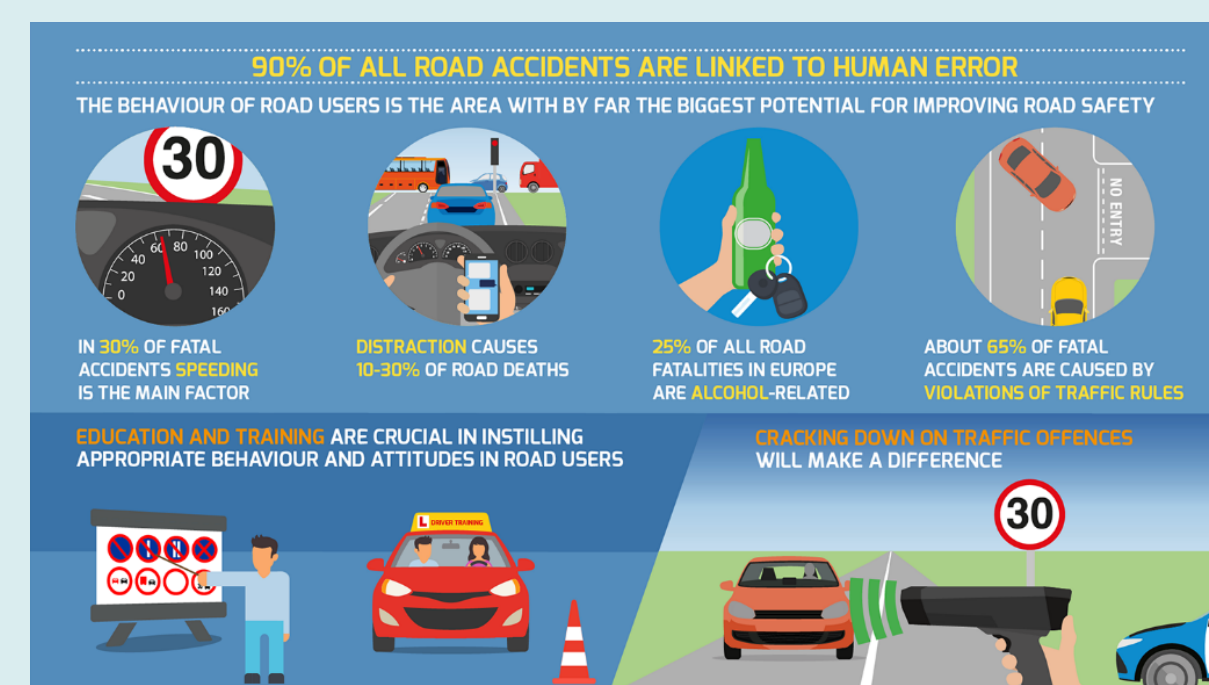
[2] Ferreira, E., Fernandes, P., Bahmankhah, B., & Coelho, M. C. (2021). *Micro-analysis of a single vehicle driving volatility and impacts on emissions for intercity corridors.* International Journal of Sustainable Transportation, 1-23. <https://doi.org/10.1080/15568318.2021.1919797>

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Graphical Abstract: Integrated research focused on:

Road Safety



<https://roadsafetyfacts.eu/what-role-do-road-users-and-infrastructure-play-in-improving-safety/>

Pollutant emissions



https://ec.europa.eu/environment/efe/news/reducing-motor-vehicles-co2-emissions-2014-03-27_en

Motor vehicles VRU interactions



https://www.123rf.com/photo_90996787_stock-vector-city-with-cars-cyclists-and-pedestrians-illustration-.html

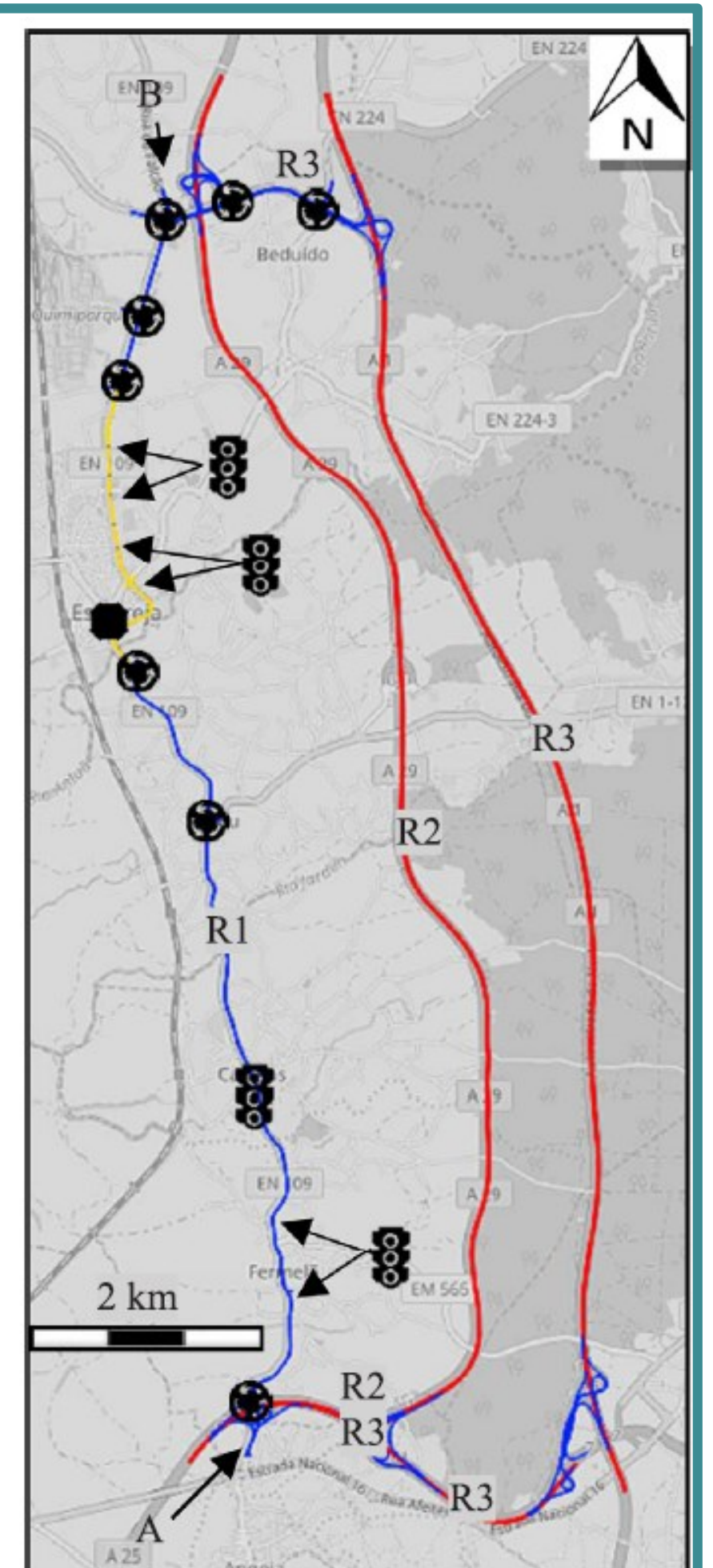
Preliminary results

| Vehicle ID | Emission Standard | Vehicle Category ¹ | Model Year | Engine Size (L) | Odometer reading at test start (km) |
|------------|-------------------|-------------------------------|--------------|-----------------|-------------------------------------|
| V1 | Euro 4 | M | June 2006 | 1.8 | 180 000 |
| V2 | Euro 6b | B | January 2017 | 1.2 | 32 000 |
| V3 | Euro 6b | C | July 2017 | 1.6 | 23 000 |
| V4 | Euro 6b | B | March 2018 | 1.5 | 25 000 |

¹ Categorization of vehicles is based on EC (1999): B – Small Cars; C – Medium Cars; M – Multi-purpose cars

- Naturalistic data:
 - ✓ A1, A29, N109 – Angeja-Estarreja and Estarreja-Angeja
 - ✓ 4 vehicles.
- Measured/computed parameters:
 - ✓ Speed, acceleration, engine power, fuel consumption, altitude, distance, vehicular jerk (first derivative of acceleration), Vehicle Specific Power mode;
 - ✓ CO₂, NO_x

Figure 1: Case study: R1 corresponds to N109 with urban and rural zones: it has traffic lights, roundabouts and stop-intersection, R2 corresponds to A29 and R3 corresponds to A1. (more details in [1]).

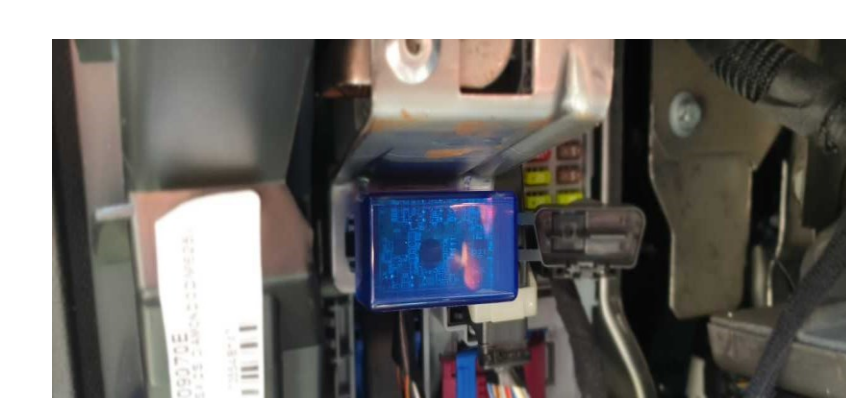


3DATX parSYNC® integrated PEMS



CO₂ (%), NO, NO₂, (ppm)
coarse PM (approximately 2.5 µm to over 10 µm), fine PM (0.3 µm to 2.5 µm), ultra-fine PM (up to 0.4 µm – 0.5 µm) – **each second**

ELM327 Bluetooth OBD-II



OBD speed; RPM; engine load; fuel flow rate; mass air flow; air-to-fuel ratio; engine volumetric efficiency – **each second**

20 571 seconds of collected data (**355 km** of road coverage)

Figure 2: Equipment's used in data collection and total of valid data under study (more details in [2]).

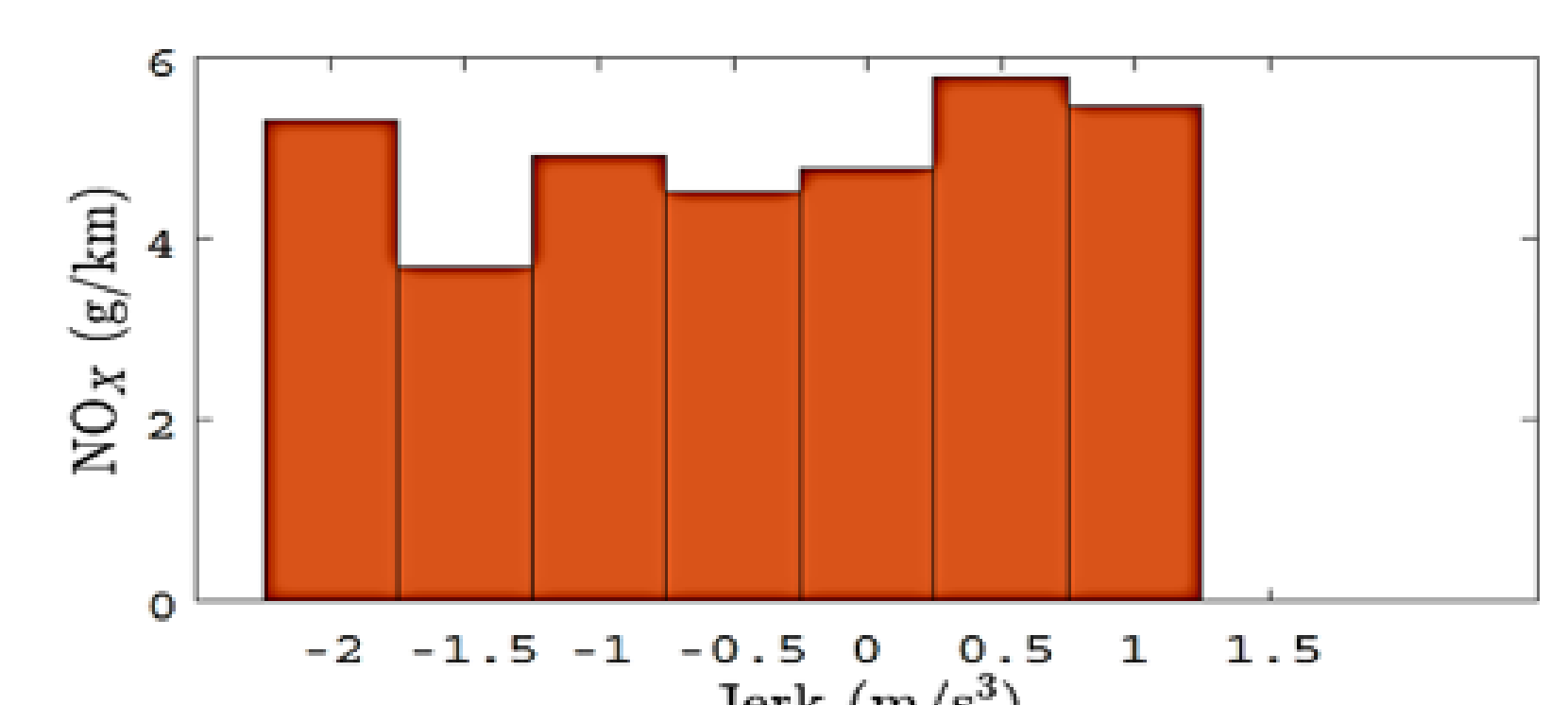
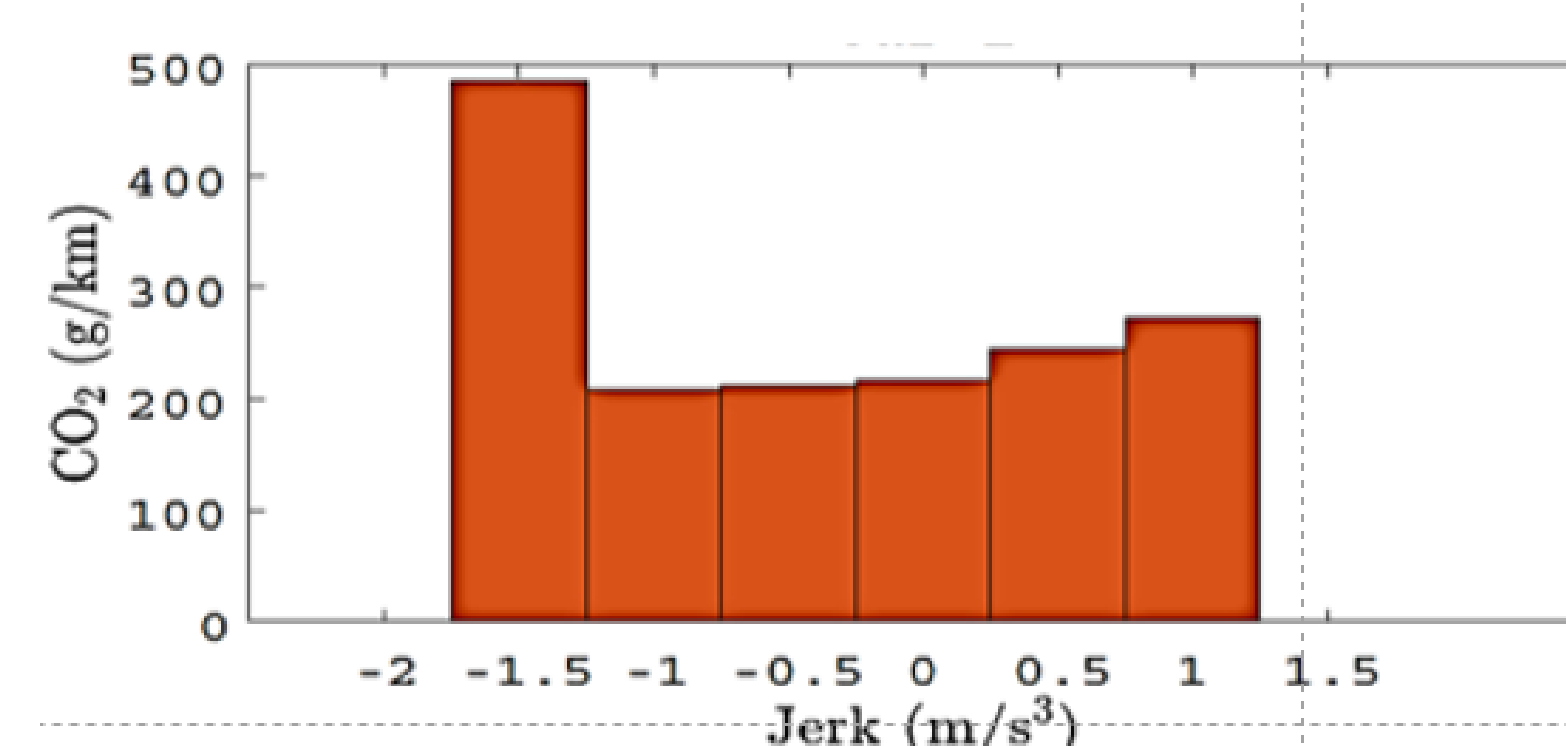


Figure 3: Accumulated CO₂ (g/km) and NO_x (g/km) by jerk frequency for V1 on route A29. For this driver, it can be observed that accumulated CO₂ and accumulated NO_x reached both high values from negative to null jerk classes. This trend also appeared in all studied cases. Negative jerk is considered dangerous because it increases the risk of a shockwave. (more details in [2])

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