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Learning from the real-world: Insights on light-vehicle efficiency and CO_2 emissions from long-term on-board fuel and energy consumption data collection ☆

Alessandro Tansini [a], Andres L. Marin [b], Jaime Suarez [a], Nestor F. Aguirre [c], Georgios Fontaras [a,*]

[a] European Commission Joint Research Centre, Ispra 21027, Italy
[b] Universitat Politècnica de València, VRAIN, Valencia 46022, Spain
[c] Independent Researcher, Amsterdam, the Netherlands

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ABSTRACT

This study explores the potential of On-Board Fuel and energy Consumption Monitoring (OBFCM) and telemetry to bridge the knowledge gap in real-world vehicle usage and fuel/energy consumption. Driving data from 50 light-duty vehicles with different technologies was collected over-the-air through OBD dongles and analysed (data is made available online), highlighting elements of vehicles real-world operation complementing the official OBFCM datasets. Fuel and energy consumption metrics are presented for the vehicle technologies captured, together with an analysis of the real-world factors affecting them. Internal Combustion Engine Vehicles (ICEVs) and Mild Hybrid Electric Vehicles (MHEVs) are mostly affected by urban driving, with a fuel increase of up to +1.20 l/100 km. Hybrid Electric Vehicles (HEVs) and Plug-in Hybrid Electric Vehicles (PHEVs) are mostly affected by motorway driving, with an increase of +1.26 and +3.85 l/100 km respectively. Extreme ambient temperatures affect ICEVs and MHEVs (up to +1 l/100 km) less than HEVs and PHEVs (+1.5 l/100 km and more). Distance statistics are also analysed in terms of daily driven distance distribution, total annual distance and shares between different driving conditions (urban, rural and motorway). PHEVs charge sustaining and pure electric driving consumption are presented together with details on the charging events. Real-world hints on the utility factor concept are discussed. Our PHEVs corporate users consume more compared to private users because of lower charging applied. The findings highlight how OBFCM provides accurate real-world data, crucial for accelerating greenhouse gas emissions reduction and energy consumption improvements.

1. Introduction

Transportation remains a focal point in the battle against climate change, with road transport being the most significant contributor to Greenhouse Gas (GhG) emissions comprising around 28.9 % of the total transport emissions in Europe. Light-Duty Vehicles (LDVs) represent an important case study, with passenger cars and vans accounting for 43.3 % and 8.8 % of total road transport GhG emissions, respectively [1]. In response to escalating concerns regarding climate, new policy measures are being implemented worldwide. The European Union (EU) is at the forefront of this effort [2], and adopted ambitious CO_2 emission targets for its road vehicle fleet [3–5]. Manufacturers are compelled to comply with stringent annual emission limits for their new vehicle sales, in an effort to reach zero tailpipe emissions for cars and vans registered in

Abbreviations: AC, Alternated Current; BEV, Battery Electric Vehicle; CAN, Controller Area Network; CD, Charge Depleting; CI, Charge Increasing; CS, Charge Sustaining; EC, Energy Consumption; ECS, Euro Car Segment; EU, European Union; FC, Fuel Consumption; GhG, Greenhouse Gas; HEV, Hybrid Electric Vehicle; ICEV, Internal Combustion Engine Vehicle; IT, Information Technology; ITID, InfoType ID; JRC, Joint Research Centre; LDV, Light Duty Vehicles; MHEV, Mild Hybrid Electric Vehicle; OBD, On-Board Diagnostics; OBFCM, On-Board Fuel and energy Consumption Monitoring; PE, Pure Electric; PHEV, Plug-in Hybrid Electric Vehicle; PID, Parameter ID; RW, Real-World; SAE, Society of Automotive Engineering; SoC, State of Charge; UF, Utility Factor; WLTC, Worldwide Harmonised Light Vehicles Test Cycle; WLTP, Worldwide Harmonised Light Vehicles Test Procedure.

☆ The views expressed in the paper are purely those of the authors and should not be interpreted as an official position of the European Commission

* Corresponding author.
E-mail address: georgios.fontaras@ec.europa.eu (G. Fontaras).

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Europe from 2035 and onwards. However, these targets are currently based on official CO_2 emission values derived from controlled laboratory tests during type-approval certification procedures [6]. On the other hand, real-world driving conditions involve a combination of factors influencing energy consumption, that often deviate significantly from the laboratory-controlled scenarios, leading to on-road Fuel Consumption (FC) and Energy Consumption (EC) values that diverge from the official figures [7–9].

Since the real-world conditions causing the gap cannot be fully incorporated in the laboratory tests, the most suitable alternative approach consists in collecting FC and EC values directly from vehicles in actual operation. In terms of real-world data collection, different studies have explored the challenges associated with the collection and regulation of real-world FC. Research conducted by Mock et al. [10] and by Pavlovic et al. [7] have consistently revealed a notable discrepancy between fuel consumption figures obtained from laboratory tests and those recorded in actual driving scenarios. This variance is ascribed to factors that can be categorised into three principal groups: (1) vehicle characteristics, which encompass the specific configuration of the vehicle [11]; (2) environmental and traffic conditions [12]; and (3) driver-related factors, including the individual's driving behaviour [7,13,14].

Despite advances in laboratory tests, the FC gap between the type-approval and the actual driving conditions still represents a concern [15]. This discrepancy is primarily due to the inability of controlled laboratory tests to fully replicate the diverse and dynamic nature of real-world driving scenarios. When Plug-in Hybrid Electric Vehicles (PHEVs) are considered, the discrepancy becomes even bigger as a consequence to the freedom that this technology offers in terms of energy source to be used, fuel or electric energy [16]. Consequently, there is a pressing need for accurate real-world data to better understand and mitigate this gap. On the accuracy topic, quality of the data is a key aspect, since for a proper assessment of fuel usage in the real-world diverse driving patterns and ambient conditions are to be covered [15]. Self-reported fuel data, despite its usefulness and large availability, may inadvertently lead to a skewed dataset [17]. This is because individuals with a heightened awareness of environmental issues or those more concerned with fuel costs are potentially more inclined to monitor and disclose their fuel usage habits [9].

To address some of these open points, the EU requires all new vehicles registered from 2021 and onwards to be equipped with technology to collect the vehicle's lifetime travelled distance and fuel consumed, with additional parameters for plug-in hybrid vehicles [3,18]. This information is delivered using standard communication protocols through the OBD-II, a system that provides information about the status of various subsystems of the vehicle, especially regarding fuel injection and tailpipe emissions [19]. These parameters are commonly known as On-Board Fuel and energy Consumption Monitoring (OBFCM) data [6]. These can accurately describe the FC from each vehicle in Europe and therefore show the real-world CO_2 emissions footprint of the vehicle fleet [20,21]. Dornoff et al. [15] and Plötz et al. [22] favour the development of rigorous and uniform methods for gathering FC data, identifying OBFCM as a particularly suitable approach.

Regulation (EU) 2021/392 [23] establishes the ways in which this information is (1) collected by the manufacturers and workshops carrying out periodical technical inspections and (2) submitted to the European Commission. According to the same regulation, OBFCM readouts from individual vehicles are to be reported on a regular basis either through manufacturers' or member states' reporting [18,24]. The first pathway foresees that manufacturers collect OBFCM parameters from their fleets through their workshops network, at vehicle maintenance and repair, or through direct transmission from vehicles to their IT systems. The second pathway foresees that member states collect OBFCM data through roadworthiness tests. These pathways not always allow for regular data sampling, since the readout might be taken physically from the vehicle when this undergoes service or maintenance, sometimes following uneven intervals. For example, vehicle service might take place after 1–2 years since registration or at mileage targets (15 k, 30 k, 45 k, etc.), depending on the vehicle model and usage (how fast it accumulates distance). Similarly, roadworthiness tests intervals depend on factors such as the country, vehicle category, age and yearly mileage, and in most cases will not produce OBFCM readouts during the first 2 years in a vehicle's lifetime [25].

This study aims to bridge part of the information gap created due to the sporadic nature of the official EU OBFCM sampling. To do so, the study is based on targeted sampling of vehicles operating in real-world conditions for which continuous data are collected systematically, to gather further insight on the underlying factors influencing the EU-wide macro sampling. The objective is to shed light on the FC variability due previously mentioned real-world factors, although conclusions are to be drawn carefully due to the low number of sampled vehicles. As it will be presented in the following sections, this is achieved by combining the collection of OBFCM data from individual vehicles, to precisely assess FC and EC, together with continuous telemetry data from the OBD-II, to define the real-world conditions under which the vehicles are operated. Cheap and nonintrusive programmable devices are employed, to be connected to the OBD-II port of vehicles and equipped with a cellular module for wireless data transfer. The monitoring of vehicle operation takes place on a long time scale, from a few months, in most of the cases, to a few years, ensuring the collection of a diverse set of conditions across several regions and boundary conditions, and for different vehicle types and powertrains. This approach has several advantages, with the main one being the collected data reflecting real-world driving, where drivers operate in their familiar environment and conditions, using their own vehicle (no bias related to the drivers having to adapt to a test vehicle that differs from their own private vehicles). FC and EC data are complemented by telemetry data sourced from the vehicle, enriching the value of the dataset and enabling deeper analyses on the vehicle/powertrain operation and the link with ambient factors, meanwhile keeping the system nonintrusive to the vehicle and to the user. The approach also enables scaling up to a larger number of monitored vehicles, as once the IT architecture is in place this would only require a larger number of programmable OBD-II devices with limited added cost.

Thus the data and analysis presented in this paper allow for a focused, precise, and holistic understanding of real-world vehicle performance and fuel efficiency that complements the EU's central collection of OBFCM data. The two datasets combined can facilitate informed decision-making, emissions and energy consumption modelling, while also providing precise and insightful feedback on how vehicles are used in the real-world in terms of daily driving habits and conditions encountered. The richness of the data, either in terms of available quantities and number of technologies covered, represents a key novelty of the study, particularly for the EU, where similar studies are based usually on a much more limited vehicle sample.

2. Material and methods

The study utilizes data from various sources, primarily focusing on OBFCM systems as detailed in the section below. Various OBFCM implementations at vehicle-level have been validated by the JRC's Vehicle Emissions Laboratories (VELAs). Additionally, this section discusses the IT infrastructure and methodologies used for data collection and processing.

2.1. On-board fuel and energy consumption monitoring

On-board fuel and energy consumption systems were introduced to continuously measure and store fuel consumption on most new vehicle cars and vans in the European fleet since 2021. These consists of physical hardware and/or integrated algorithms within the vehicle's existing systems.

OBFCM devices make data available for readout through the On-

Board Diagnostics (OBD) hardware and standard (SAE J1979). On any vehicle equipped with OBFCM (from EURO standard 6 AP), and at any point in time, it shall be possible to read the OBFCM parameters listed in Table 1 through simple and standardised OBD queries similar to the ones to collect the normal Parameter-IDs (PIDs) and trouble codes made available by vehicle diagnostics. In fact, the instantaneous signals presented in the first column of Table 1 are normal PIDs from OBD service 01 (ISO 15031-5, "show current data") used to obtain real-time information such as engine rotational speed, coolant temperature or other engine/vehicle parameters.[1]

It is important to specify how the engine fuel rate in g/s differs from the vehicle fuel rate in g/s: the latter includes fuel injected in the after-treatment system, if any. Signals from the second and third columns are obtained through OBD service 09 (ISO 15031-5, "Request vehicle information") and are defined as Info Type IDs (ITIDs), but despite the different naming the collection mechanism through OBD is very similar. With the adoption of ISO 27145-2, the two services will eventually be migrated to service 22 ("Read data by identifier"). The presented lifetime parameters represent a key innovation in the on-board data monitoring, since these signals require new algorithms to monitor vehicle operation and produce cumulative parameters with accuracy requirements.

According to United Nations Regulation No. 154 (UN R154), OBFCM parameters shall be the most accurate values from the measurement and calculation system of the engine control unit. Unfortunately, this just specifies that the best on-board data available is channelled through OBFCM regardless of its actual quality. Out of all the parameters, only the total fuel consumed lifetime signal is checked for accuracy:

$$Accuracy = \frac{Fuelconsumed_{WTLP} - Fuelconsumed_{OBFCM}}{Fuelconsumed_{WLTP}}$$

where $Fuelconsumed_{WTLP}$ is the fuel consumed over a WLTP cycle in litres from carbon balance method and $Fuelconsumed_{OBFCM}$ is the increment in the lifetime fuel consumed parameter on OBFCM. Accuracy has to fall within −0.05 and +0.05 (5 % error). Such condition shall be fulfilled either at the first WLTP test, or by carrying out additional WLTP tests until the accuracy is obtained on the cumulative fuel volume (maximum three additional tests can be carried out). If the vehicle represents an intermediate vehicle within an interpolation family, the additional tests are to be carried out both on vehicle low and vehicle high.

Table 1
Mandatory data on OBFCM-compliant vehicles.

Instantaneous signals (PIDs)	Lifetime signals (ITIDs)	Lifetime signals (ITIDs) - PHEVs only
vehicle speed (km/h)	total distance travelled (km)	total distance travelled in charge depleting operation with engine off (km)
engine fuel rate (l/h)	total fuel consumed (l)	total distance travelled in charge depleting operation with engine running (km)
engine fuel rate (g/s)		total distance travelled in driver-selectable charge increasing operation (km)
vehicle fuel rate (g/s)		total fuel consumed in charge depleting operation (l)
		total fuel consumed in driver-selectable charge increasing operation (l)
		total grid energy into the battery (kWh)

[1] Within the test activities carried out at JRC over the past few years, some vehicles were found that made these PIDs available even before OBFCM was introduced. Their availability is now mandatory by law. The engine fuel rate in l/h enables for the straightforward calculation of the total litres of fuel consumed through a simple time integration. To calculate the same quantity through the other two signals, an assumption on the fuel density would have to be made. Vice versa, one could calculate the fuel density assumed by the vehicle as the ratio between the mass-based and the volume-based engine fuel rates.

2.2. Vehicles and measurements

OBFCM data were recorded from 50 vehicles (vehicle sample) belonging to different Euro Car Segments (ECS) and body styles (hatchback, sedan, station wagon, minivan, SUV), as classified according to Laveneziana et al. [11]. This classification establishes a clear link with the vehicle energy consumption and CO_2 emissions characteristics with the attributed car segments presented in Table A1 in Appendix A. The vehicle sample included different powertrain technologies and electrification levels, from none to the highest, from those currently within scope of OBFCM: Internal Combustion Engine Vehicles (ICEVs), Mild-Hybrid Electric Vehicles (MHEVs), Hybrid Electric Vehicles (HEVs) and Plug-in Hybrid Electric Vehicles (PHEVs) (info in Table A1 in Appendix A). To preserve anonymity and respecting data privacy requirements, each vehicle will be henceforward named after a constellation.

Depending on the type of usage, vehicles belong to the following categories that can impact the captured real-world performance: private, corporate, rental and test vehicles. The first category contains vehicles owned by private persons, who actively chose a vehicle model and technology according to their taste and driving needs. The second category contains vehicles sourced by companies for their employees, mainly for the fulfilment of their duties. In such a case, users might have to choose from a limited pool of models, possibly implying no active role in the powertrain selection, but most importantly they don't bear vehicle procurement costs. The third category contains vehicles that drivers rented just for a short period of time from a rental company. Lastly, the fourth category contains vehicles rented by the JRC and used for different purposes including vehicle emissions tests; for this reason, the collected data might require careful cleaning before usage.

Two specific vehicles from the sample were used to analyse and validate the lifetime OBFCM readouts. The first vehicle, *Draco*, a petrol C-segment hatchback PHEV, was tested in JRC's to compare OBFCM parameters with chassis dynamometer and gas analysis measurements. The second vehicle, *Volans*, a petrol C-segment hatchback ICEV, was driven on public roads while the total distance and fuel refilled to the tank at fuel pumps were carefully noted to serve as real-world benchmark of OBFCM accuracy.

All vehicles have been produced and registered from 2021 and onwards (at least EU 6 AP as emissions standard, requirement to be OBFCM equipped). Regarding their status and level of maintenance, it is assumed that vehicle services have been carried out regularly and that their fuel and energy consumption data is representative. This is confirmed for the vehicles that we monitored more closely (vehicles with user type "test" in Table A1 in Appendix A). For the remaining ones we assume that services were carried out for warranty-related reasons.

Being the sample of limited size, the goal of this study is not to generalise findings at fleet-level but rather to highlight outstanding differences between different vehicle technologies and make comparative analyses within these.

2.3. Real-world data collection and processing

Data collection is based on programmable OBD dongles with positioning systems and internet connection that read out vehicle data and transmit the telemetry data and OBFCM parameters. These OBD dongles, based on open-source hardware [26], were further developed and validated to fulfil the data collection activity requirements, regarding:

- ease of installation by non-expert users
- energy consumption minimisation to avoid service battery depletion

- reliable automatic device wake-up and stand-by at trips start and end
- 1 Hz collection of telemetry (positioning included)
- collection of OBFCM lifetime data at regular intervals (30 s)
- automatic data transfer to JRC servers.

The study team recruited volunteers from different countries including Italy, Spain, Greece, Germany, France and Belgium. The geographical span of the collected data represents an added value to the dataset, since a greater variety of driving and ambient conditions is captured.

Data are transmitted in real-time whenever a trip takes place. In addition to the OBFCM lifetime and instantaneous values from Table 1, the devices were programmed to collect other relevant information from the OBD standard such as: vehicle speed, engine speed, engine load, ambient temperature, accelerator pedal pressure and others, allowing a deeper inspection of the vehicle efficiency and the real-world usage benchmarking.

The data collection workflow involves multiple steps (see Fig. 1). Firstly, parameters are readout from the vehicle control units through the diagnostics port using OBD protocols and bundled together with GPS measurements. Cellular network is used to transmit the data bundles over-the-air to the production server (errors and data loss management explained in Appendix B). A teleserver application takes care of receiving the data bundles and writing the information to a non-sequential database. MongoDB is used to store the raw data received from the devices, and a replica database is set up to keep a copy of the primary database to further guarantee data preservation. Finally, raw data is processed applying corrections, aggregation and cleaning for later analysis. Due to the size of the dataset, these last steps are carried out on a computing platform developed at the JRC [27].

The database contains 1 Hz timeseries from real-world driving from vehicles of different powertrain technologies (ICEV, MHEV, HEV and PHEV). Data is aggregated per trip, leading to the creation of the “trips aggregated data”, the set of data used for the analysis presented in this study, including total distance travelled, total fuel consumed, average fuel consumption in litres/100 km and calculated parameters as context data to study the FC variability such as: average ambient temperature, average trip speed, share of urban, rural or motorway driving, trip dynamicity and other metrics. This dataset, together with vehicles specifications, is publicly available (see “Data availability” section).

The trip distance and the fuel consumed were obtained by calculating the OBFCM lifetime parameters increment over the trip. For some vehicles, it was not possible to read the lifetime parameters (at all, or at least in the beginning of the project) due to incompatibilities between the OBD-dongles pre-implemented OBD library (partial implementation of SAE J1979) and the CAN (Controller Area Network) identifiers of the vehicles’ control units responding to the OBFCM queries. The OBD instantaneous values for these vehicles were used instead (vehicle speed to calculate total distance, fuel rates to calculate total consumed fuel), which were found to be accurate (comparing lifetime and instantaneous values on other vehicles, but also as a result of the analysis presented in the OBFCM technology assessment section 2.4 of this study).

2.4. OBFCM technology assessment

The scope of the assessment was twofold. First, to build confidence in the capacity of the OBFCM technology to provide reliable data. A past exercise [20] had demonstrated the accuracies of proprietary fuel signals from the CAN on vehicles type-approved prior to the OBFCM introduction. To confirm the findings, the PHEV *Draco*, was tested in the laboratory and the OBFCM results were compared to those measured using the standard certification-test equipment, covering quantities that are only available to PHEVs (distance and fuel in different operating modes, grid energy charged into the battery). Second, it was important to assess the OBFCM results reliability over time and in real-world conditions, and for this purpose we monitored for an extensive period a vehicle being driven on the road, *Volans*, for which the study team had the opportunity to reliably track the actual total distance and fuel for comparison.

2.4.1. Laboratory testing

A PHEV, *Draco*, was tested in the lab to collect and analyse OBFCM data to look into the OBFCM parameters’ characteristics and reliability. PHEV is the only technology enabling a full validation, since certain OBFCM parameters (e.g. grid energy) are missing on ICEV, MHEV and HEV. The tests were performed at the JRC’s VELA labs according to the WLTP testing procedure (Regulation (EU) 2017/1151 [6]) and using certified instruments for measuring fuel consumption, energy consumption, emissions, vehicle speed, distance and other parameters relevant to the OBFCM assessment. A Charge Depleting (CD) followed by a Charge Sustaining (CS) tests were carried out. In CD mode, the battery State of Charge (SoC) decreases as the drive progresses. In CS the operation is similar to that of HEVs, with the electrical part of the powertrain used to recover braking energy, optimise the FC and maintain the state of charge in the long-term. The main findings are presented in Fig. 2.

Subplot (a) illustrates the CD-CS test sequence carried out on the vehicle, following the WLTP testing procedure. It shows the dyno-measured vehicle speed and the battery SoC on the primary y-axis (left), and the ICE speed on the secondary y-axis (right). The vehicle completed 4 WLTCs in the CD test, starting from a fully charged battery, with the 4th fulfilling the break-off criterion and hence identifying as the confirmation cycle. Therefore, the 3rd is the transition cycle [28,29].

Subplot (b) compares the driven distance according to dyno measurements (*lab_distance*), the OBD distance calculated as the integral of the OBD speed (*obd_distance*), and the OBFCM distance calculated as the increase of the OBFCM lifetime total distance (*obfcm_distance*). The three methods provide similar results, with *obd_distance* and *obfcm_distance* being on average +0.81 % and +1.63 % above the laboratory reference value, respectively.

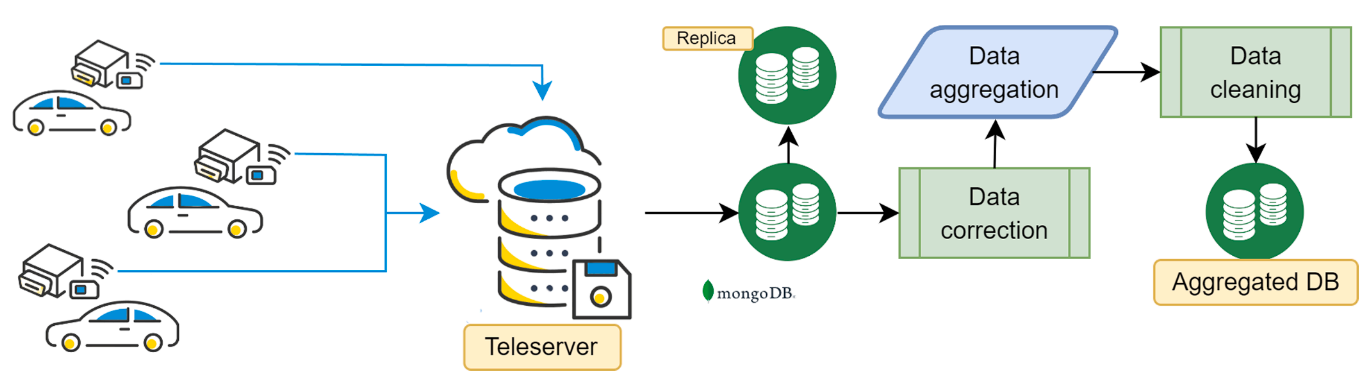

Fig. 1. Flow chart of data collection, storage and curation.

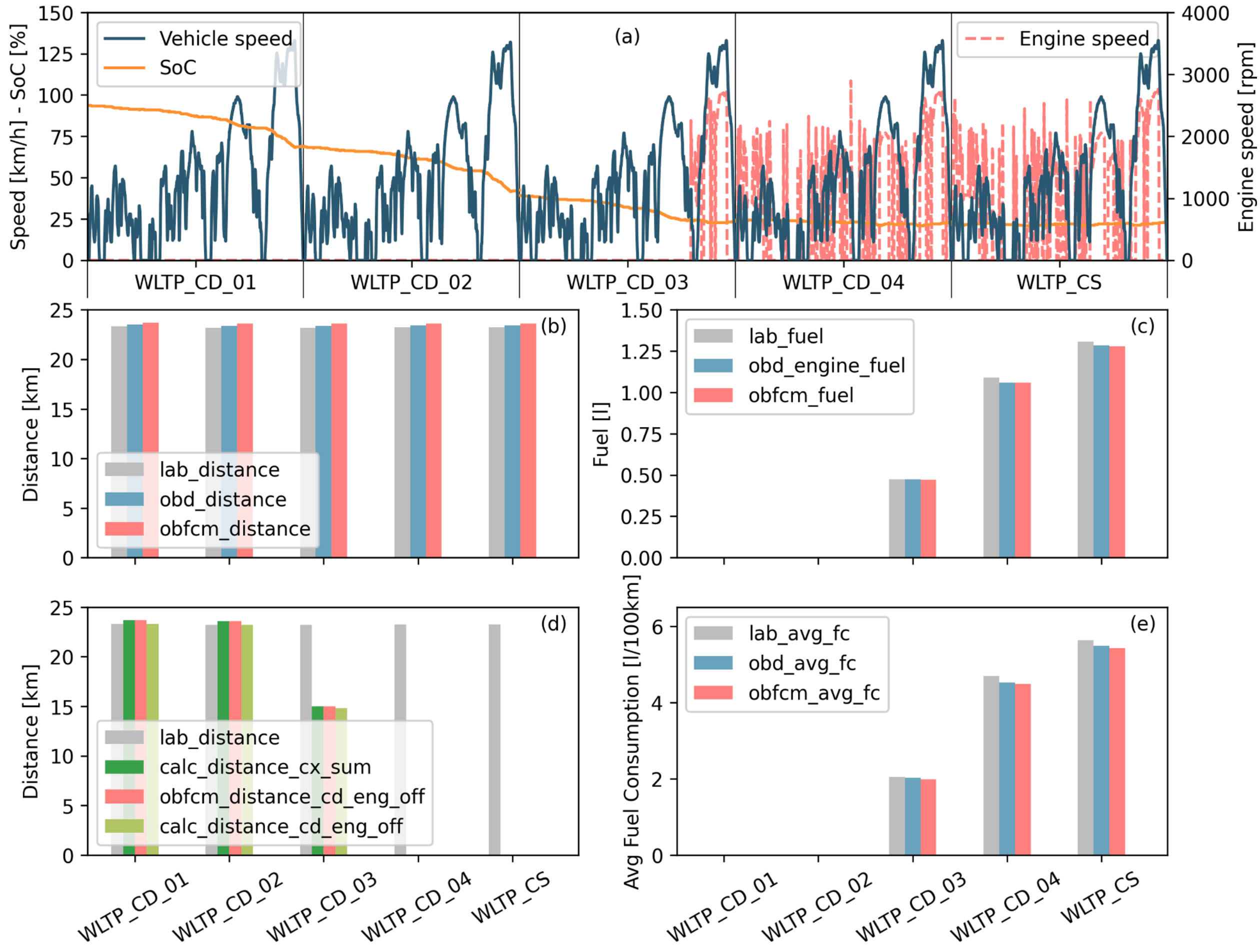

Fig. 2. Laboratory OBFCM validation following the WLTP type-approval procedure with plug-in hybrid test vehicle Draco. (a) dyno measured vehicle speed (speed), engine speed (rpm) and battery State of Charge (SoC) throughout the different CD and CS tests followed consecutively. (b) Comparison between the distance measured with laboratory equipment (lab_distance) and the distances recorded from OBD instantaneous (obd_distance) and OBFCM lifetime (obfcm_distance) parameters (c) Same comparison as (b) but on fuel consumed (d) analysis of plug-in hybrid vehicles distances driven in different operating modes (e) Comparison among laboratory-measured (lab_avg_fc), the OBD-calculated (obd_avg_fc) and the OBFCM-calculated (obfcm_avg_fc) test average fuel consumption.

Subplot (c) presents the fuel consumed according to gas analysis measurements (*lab_fuel*), the integral of the OBD PID engine fuel rate (*obd_engine_fuel*), and the increase in the OBFCM total fuel consumed (*obfcm_fuel*). The three methods again provide similar results, with *obd_engine_fuel* and *obfcm_fuel* being on average −1.68 % and −1.97 % compared to the laboratory reference in the three cycles with the running ICE. The two additional fuel rate instantaneous signals (PIDs) from Table 1, engine fuel rate (g/s) and vehicle fuel rate (g/s), were also analysed and used. On this petrol PHEV, the two parameters return the same quantity, indicating the absence of fuel injection for after-treatment. By dividing the engine fuel rate in l/h by the one in g/s, it was possible to calculate the fuel density as assumed by the vehicle's control units, obtaining a stable density of 733.26 ± 0.45 g/l.

Subplot (d) compares the PHEV-specific distances in different operating modes. The dyno-measured driven distance (*lab_distance*) is compared to the driven distance calculated from the sum of the OBFCM lifetime distance PHEV-parameters (*calc_distance_cx_sum)* detailed in Table 1: CD engine off, CD engine on and driver-selectable CI. The CD engine off distance (*obfcm_distance_cd_eng_off)*, calculated from the OBFCM lifetime increment, and the distance driven with engine off (*calc_distance_cd_eng_off*), calculated as the cumulative distance driven (integral of OBD speed) with engine at zero rotational speed, are also added to the comparison. The different parameters match closely in the first and second WLTCs where there was no ICE activation, meaning that CD engine off distance was the only OBFCM lifetime incrementing. The calculated distance with the vehicle running only on battery energy (i.e. with engine off) matches very closely the variation of the OBFCM charge depleting engine off parameter. Important to notice that CS distance and fuel appear nowhere among the PHEV-specific OBFCM lifetime values, as the SAE J1979 standard does not support them to date.

Finally, in subplot (e), the comparison of the calculated average fuel consumption is presented. The OBD-based (*obd_avg_fc*) and the OBFCM-based (*obfcm_avg_fc*) estimates are −2.45 % and −3.49 % compared to the lab-based measurement (*lab_avg_fc*), an underestimation of OBFCM fuel consumption due to the fact that distance and fuel deviations had opposite signs.

According to the Digital Annex to SAE J1979, the total grid energy into the battery variable shall not include charging losses and shall therefore reflect the total amount of energy that enters into the battery. To confirm this, a full charging event was measured in the laboratory by means of a power analyser. An Alternate Current (AC) domestic charger was used: this device connects the vehicle to a normal 220 V wall socket (10 Amperes maximum current). Both the grid energy (from the wall socket) and the battery energy (on battery terminals) were measured through voltage probes and current clamps. The results of such exercise are reported in Table 2.

The change in OBFCM total grid energy into the battery between the start and the end of the charging event matches the amount of energy measured at the battery terminals through the power analyser, with a relative error of only +0.27 %. It is important to specify that the

Table 2
Grid energy recharged to the battery.

Quantity	Value
Measured grid energy – power analyser	10.95 kWh
Measured battery energy – power analyser	9.37 kWh
Grid energy into the battery – OBFCM	9.4 kWh
OBFCM relative error [%]	+0.27 %
Charging efficiency [%]	85.6 %

resolution of this OBFCM parameter is ± 0.1 kWh i.e. the 1.067 % of the measured quantity. As a consequence, the relative error obtained is not to be taken strictly; the main takeaway from this comparison is that OBFCM appears to be very accurate towards the estimation of recharged energy on this vehicle.

The charging efficiency, calculated as battery energy divided by grid energy, is 85.6 %. This parameter is important when trying to estimate the total impact from driving PHEVs, i.e. for calculating the actual grid energy draw for each kWh of energy charged to the battery, and corresponds to the efficiency of the on-board charger.

2.4.2. On-road monitoring

The OBFCM validation was carried out also on-road to check if an accuracy level similar to the one obtained under laboratory conditions could be obtained. The vehicle *Volans* was therefore monitored throughout its lifetime (since vehicle registration in February 2022). In the time span analysed (February 2022-November 2023) *Volans* drove for roughly 16000 km and its tank was refilled to its maximum capacity 17 times (see Fig. 3), enabling the same number of comparisons with OBFCM lifetime parameters readouts. Any time that the tank would be refilled to the maximum, the odometer and litres added to the tank were noted down. The delta odometer was then compared with the delta OBFCM total distance, and the litres added to the tank with the OBFCM total fuel. All the fuel readings remained in the tolerance of ± 5 % as prescribed by the regulation, apart from one single fuelling event associated with a fuel error of −9.7 %. The reason behind the discrepancy is unknown; this could also be attributed to a wrong feedback from the fuel pump, or represent an isolated case that doesn't hamper the effectiveness of OBFCM technology over a vehicle's lifetime. The relative difference on distance was on average −0.8 % with a standard deviation of 0.5 %, while on fuel was on average –2.1 % with a standard deviation of 2.7 %. The relative difference on the calculated average fuel consumption from OBFCM was –1.3 % with a standard deviation of 2.5 %. Despite a slight tendency to underestimate the real-world average fuel consumption, the OBFCM data collected from Volans seems to be reliable and fully in line with the accuracy expectations of the OBFCM scheme.

3. Results and discussion

3.1. Collected data

An overview of the captured data is provided in Table 3 presenting for each vehicle technology the number of vehicles, the total accumulated mileage and the total number of days captured. A considerable amount of data was collected for each technology. The lifetime coverage and the OBFCM data from each vehicle are presented in Fig. 4.

The four subplots on the left side present the first and last OBFCM readouts for distance (x-axis) and fuel (y-axis). A connecting straight line is added for better visualisation. The four subplots on the right present the comparison of the average FC calculated using only the most recent lifetime value (x-axis) versus the one calculated from the first and last readouts (y-axis) in our captured data.

Table 3
Summary of the vehicles technology and of the amount of data captured for each type of technology (until October 2024 included).

Type	Vehicles [-]	Captured distance [km]	Days-vehicle [-]
ICEV	21	262,022	3708
MHEV	11	92,168	1486
HEV	7	49,188	954
PHEV	11	109,164	1932
Total	50	512,544	8080

Fig. 3. Road validation of OBFCM total distance and total fuel parameters on Volans. Data collection supervised by the study team. (a) distance relative error between OBFCM and odometer increment (b) fuel relative error between OBFCM and fuel volume from refuelling (c) average fuel consumption error between OBFCM and real-world calculations.

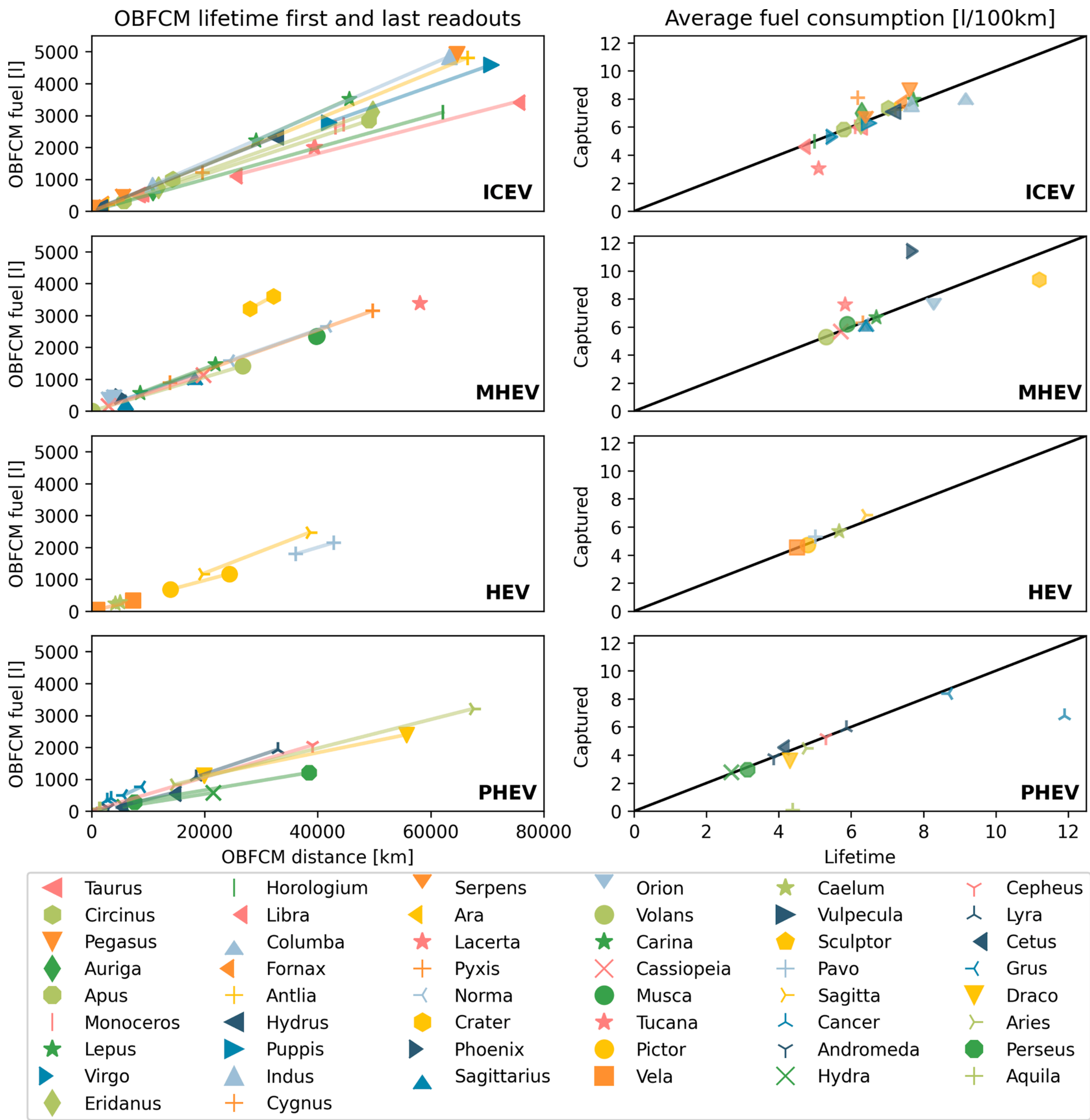

Fig. 4. Overview of the captured data per vehicle technology (from top to bottom: ICEV, MHEV, HEV, PHEV). Left subplots show the first and last OBFCM distance and fuel readouts of the observation campaign for each vehicle, where each vehicle is represented by a different symbol with a segment connecting both readouts. Right subplots compare the average fuel consumption obtained from the last lifetime OBFCM value (lifetime average) and the one calculated from the increase during the observation period (captured data average).

This comparison shows whether the FC data captured during the monitoring period are similar to the values retrieved over lifetime value of the vehicle and screen out outliers or cases where deviations may exceed certain limits, indicating equipment malfunctions or data loss. Overall, these FC values match very closely for all vehicles with few exceptions. These exceptions are most likely caused by the monitoring period being much shorter than the vehicle lifetime, therefore more subject to the trips FC variability in the period.

Despite a problem related to technical incompatibilities between the OBD dongles and some of the HEVs that prevented the collection of lifetime values in the earlier stages of the project, the OBFCM instantaneous fuel rates were successfully used for the calculation of the total distance and fuel consumed. Later on in the project this technical limitation was solved, and lifetime values were regularly collected on all vehicle technologies. Hence the representation of HEVs data availability in Fig. 4 is actually bigger than what it appears to be. Table 3 provides information from all captured trips.

3.2. Fuel consumption

3.2.1. Fuel consumption and speed distribution

Variability in FC and trips characteristics is presented in Fig. 5, containing distributions of the trip-average fuel consumption (left) and vehicle speed (right) per vehicle technology: ICEV, MHEV, HEV and PHEV, from top to bottom, with the latest category being split according to the type of user, private or corporate. Trip results are weighted according to distance (i.e. longer trips will have higher significance), which is of paramount importance to return meaningful distributions

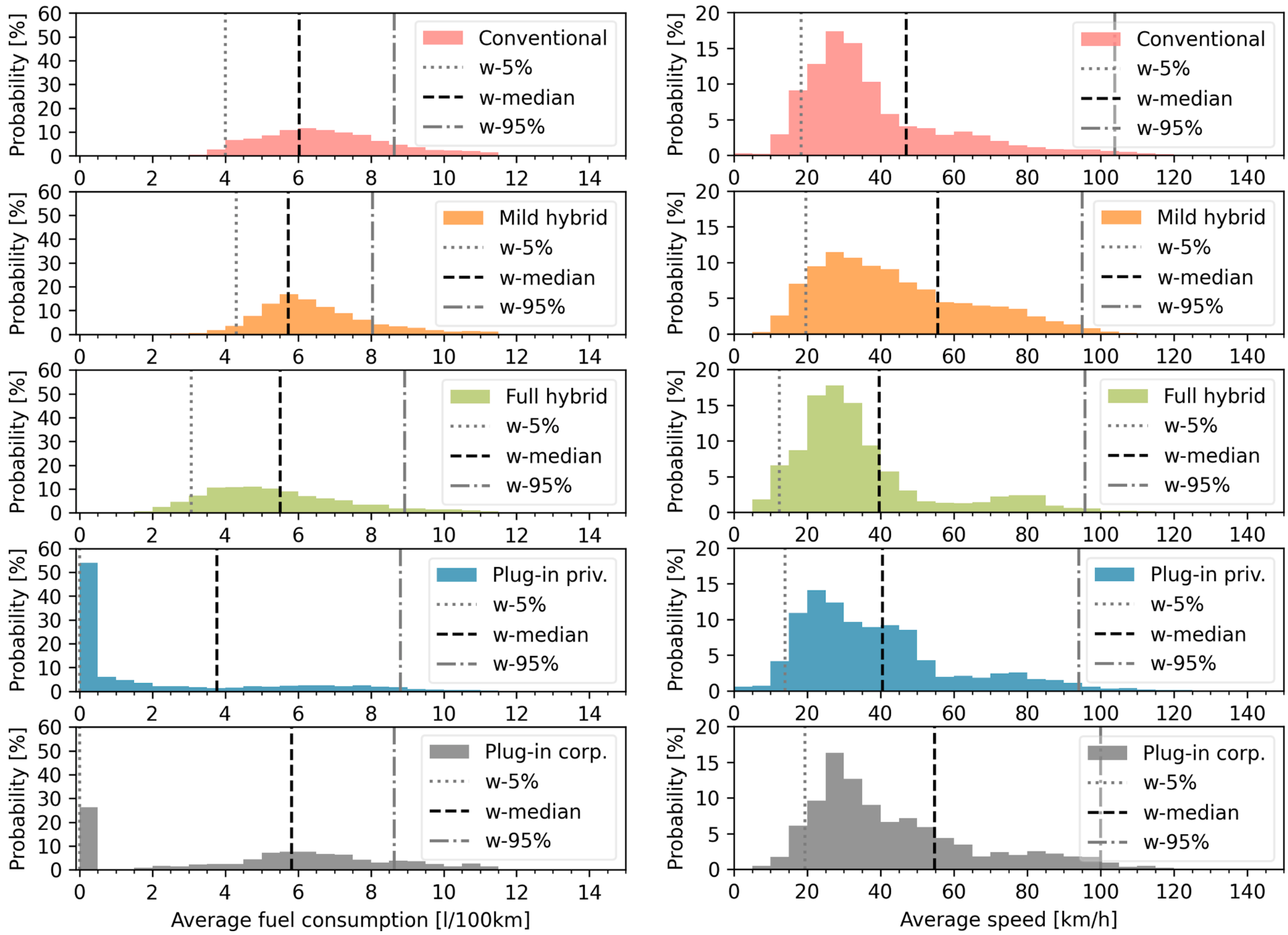

Fig. 5. Distributions of trip average fuel consumption (left) and trip average speed (right) per technology (and user type for PHEVs). Distance weighting is applied to the trips (higher significance to longer trips). Vertical dashed lines are the weighted median value, dotted lines the weighted 5th percentile (w-5%) and dot-dashed lines the weighted 95th percentile (w-95%).

reflecting the lifetime average fuel consumption, especially for PHEVs [30]. To put into perspective the fuel consumption results, trip average vehicle speed is added to the figure, as it directly influences vehicle energy demand and therefore fuel consumption [31–33]. For each distribution, the distance-weighted median (w-median), 5th and 95th percentiles (w-5 % and w-95 %) are visualised through vertical lines.

The medians of the distance-weighted (w-median) trip average fuel consumption distributions can be used as representative FC values (lifetime, average from different vehicles) to compare the different powertrain technologies and user categories. Moving from top to bottom, higher hybridisation (i.e. electrification) degrees are found: from ICEVs, i.e. no hybridisation, to MHEVs, i.e. mild hybridisation, to HEVs, i.e. to more significant hybridisation, and finally to PHEVs, which are capable of driving several km on battery energy only. Lower FC is found for higher hybridisation levels. ICEVs and MHEVs show very similar FC distribution ranges, approximately from 3.5 l/100 km to 10.0 l/100 km. Regarding HEVs, the FC distribution becomes significantly broader, encompassing FC from 2 l/100 km to 10 l/100 km. The upper percentile (w-95 %) shifts to higher values for reasons that are hard to find from a high-level analysis. The difference might come from the different speed distribution that here presents two modes, one for low urban speeds (20 – 40 km/h) and one for intermediate rural speeds (80 km/h). Additionally, outside of the trips characteristics and driving style, a possible explanation is the powertrain control strategy adopting a battery charge strategy in certain trips and a battery depleting one in other trips effectively widening the trip FC variability, as suggested by the lower percentile (w-5 %) moving down to 2 l/km, values that can hardly be achieved by the most efficient ICEVs and MHEVs.

The last rows of Fig. 5 present the distributions for private and corporate-owned PHEVs, where an interesting pattern emerges for FC since two modes are identified. The first peak at very low FC values (below 0.5 l/100 km) corresponds to trips driven mostly in electric mode (CD), while the second one takes places at values where the operation mode is mostly ICE-supported (CS, between 4 l/100 km and 10 l/100 km). In our sample, private and corporate PHEV users exhibit very different distributions under this aspect (high share of CD for private PHEVs, CS for corporate PHEVs). According to the median value of the FC distribution for private users, PHEVs could be considered a promising market-ready solution in terms of fuel consumption and tailpipe CO_2 emissions, with savings close to 50 % when appropriate usage is applied to unveil their potential. Meanwhile, PHEVs from corporate users in our sample exhibit an FC value almost as high as the ICEVs one, raising concerns around the real-world CO_2 savings when the vehicle usage is decoupled from the procurement and operational costs.

These results highlight, as a previous studies have pointed out [8,16,29], the tight dependency between the way PHEVs are used in the real-world and the FC; as it will be discussed in the PHEV-dedicated section, this is highly influenced by charging practices. Various hypotheses can be made on the reasons behind the FC difference. Corporate users are not required to bear the vehicle procurement costs (as for the drivers in our sample), differently from private users who are motivated towards reaching the break-even point where the extra upfront cost of a PHEV is compensated by lower in-service costs (i.e. by running the vehicle on electric energy, when this is cheaper than fuel). Corporate users might also get fuel costs reimbursed, whereas schemes to pay for the electric energy at chargers might be missing [34], and in any case these might not be enough to motivate users to spend time at a charger to add just a few km (50–70) of electric range during a busy day, compared to the hundreds that are added by a refuelling event. In addition to the costs motivations, the private user who actively chose to be driving a PHEV might be more inclined into a more eco-friendly mobility. For both these reasons, not only a private PHEV user might try to keep the vehicle as charged as possible but might also try to be more efficient while driving, by adopting good driving practices enabling energy savings (e.g. sailing, exploitation of the kinetic energy, limiting maximum speed, etc.) and reducing the usage of on-board auxiliaries; this has been confirmed by some of our drivers, and can take part to follow-up analyses where the driving is analysed in greater detail from the 1 Hz driving data. Speed distributions in Fig. 5 suggest that the hypothesis may be right, showing private users driving at slower speeds compared to corporate users. Further corporate versus non-corporate usage differences are discussed in the PHEV-dedicated section. Based on the difference in real-world CO_2 emissions highlighted and the underlying reasons discussed in other studies [22,35], PHEVs used by corporate users will be treated separately in the targeted analyses presented in the next sections. These will also discuss the impact of additional factors such as the distance driven per day or in a year, the ambient temperature or the vehicle speed.

3.2.2. Fuel data analysis

The OBFCM instantaneous data allow for the calculation of fuel density. It is important to clarify that the result is not necessarily the actual density of the fuel but might in reality reflect the assumptions included in the individual vehicle controller calibrations for estimating the OBFCM values. The fuel density was calculated from each trip by integrating the engine fuel rate in grams per second and dividing by the integral of the litres per hour engine fuel rate. This calculation was carried out for all the trips within the dataset of trip aggregated data. The median of the density values obtained on each vehicle was then calculated. The results from this analysis are presented in Fig. 6.

Compared with standard fuels density ranges (referred to 15 °C), i.e. EN228 for petrol with values spanning from 720 kg/m^3 to 775 kg/m^3, the calculated density values for petrol cars we monitored are in the same range but slightly biased towards low density values. For diesel, the EN590 standard foresees a range between 820 kg/m^3 and 845 kg/m^3, while the distribution from the monitored vehicles is in some cases clearly below the lower limit.

For most of the vehicles, the calculated trip density was found to be pretty stable around a centre value, with some noise that was either introduced by the data collection mechanism or by different vehicle or ambient conditions. With respect to the latter, only for one vehicle in the sample the calculated trip density was found to be linearly correlated to the ambient temperature, with lower densities obtained at high temperatures. No other outstanding correlations with physical quantities or trip statistics were identified.

The difference between engine fuel rate and vehicle fuel rate was also analysed by comparing their integrals. Only for three vehicles the fuel consumption at vehicle-level resulted to be bigger than the engine-level one, with a discrepancy of +1.82 % (*Orion*), +4.96 % (*Fornax*) and +12.94 % (*Antlia*), respectively, in increasing order. All these vehicles are equipped with diesel engines and produced by the same manufacturer, hinting either at a specific after-treatment control strategy or some other implementation property that affected the OBFCM instantaneous parameters. For the remaining vehicles the engine and vehicle fuel rate integrals matched perfectly.

3.3. PHEVs

3.3.1. Charging and impact on fuel consumption

To understand fuel consumption variability in PHEVs, one needs to consider the electric energy consumption together with the charging frequencies as presented in Fig. 7 for the PHEVs subset in which data was available for this analysis (remaining ones dropped because of missing data). In addition to private and corporate PHEVs, test vehicles *Draco* and *Andromeda* were used in this analysis.

The left subplot of Fig. 7 presents FC in l/100 km against the battery

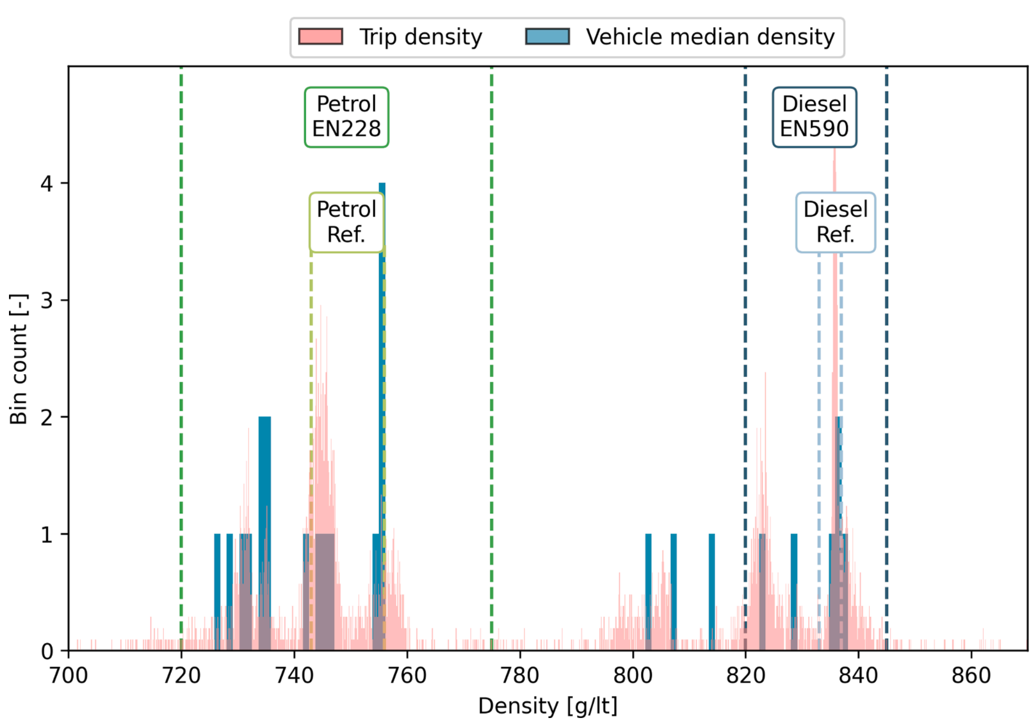

Fig. 6. Histogram of trip and vehicle median fuel density in grams per litre as calculated from the instantaneous fuel rates.

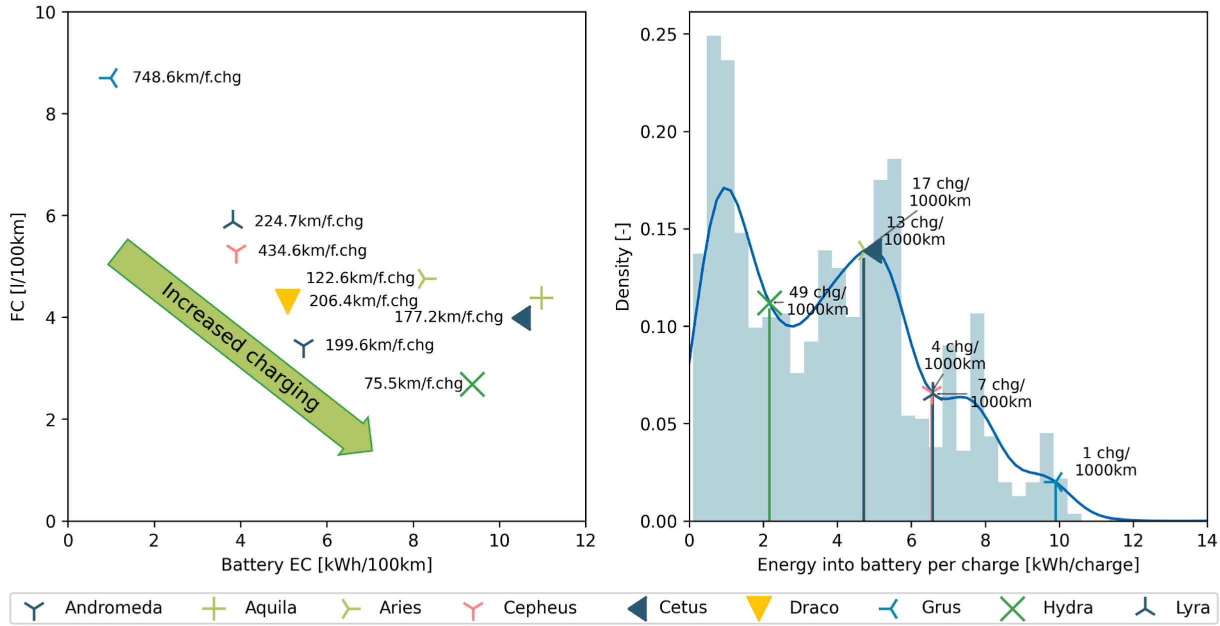

Fig. 7. Left subplot – PHEVs lifetime average FC and battery EC distance, text labels report the average distance in between two full charging events. **Right subplot** – histogram of the energy into battery from all the captured charging events, vehicles' markers and text labels reporting the average energy into battery per charge (per vehicle, x-coordinate) and the average number of charging events per 1000 km. Acronyms: chg = charge(s).

EC in kWh/100 km. The text labels include the average distance in between two full charging events i.e. the total distance captured on the vehicle divided by the number of equivalent full charging events (that differs from the number of actual charging events). The lifetime average FC and EC largely depend on the real-world Utility Factor (UF), i.e. in first approximation to the ratio of lifetime distance driven on energy from the external charge [6,28]. In real-world usage, UF is more appropriately defined as the ratio of grid energy on the total amount of energy used by the whole vehicle (combining fuel and grid energy) in a way to include also the consumption from auxiliaries [3,36]. Vehicles that have been charged more, and presumably have a higher real-world UF, appear to the right of the plot where higher EC (x-coordinate) and lower FC (y coordinate) are found (as a consequence of higher share of electric driving), with *Hydra* being the least fuel consuming vehicle with 2.69 l/100 km and 9.4 kWh/100 km and a small distance of 66 km in between two equivalent full charges. On the other hand, vehicles that were charged less are expected to have a lower real-world UF and appear to the left of the subplot, with higher FC and lower EC values, therefore representing cases where the potential of PHEVs is not expressed. In particular, *Grus* has consumed 8.70 l/100 km and less than 1 kWh/100 km in average of battery energy and has therefore been operated in the real-world almost exclusively in fuel-consuming mode, with equivalent full charges being more than 700 km apart from each other.

The right subplot in Fig. 7 presents the probability distribution of the electric energy into the battery in each charging event. These were detected by identifying, for each vehicle, the moments when the OBFCM grid energy appeared greater than the last readout from the previous trip and the OBFCM total distance remained almost the same (i.e. a charge took place in between two subsequent trips). Additionally, the average energy into battery per charge on each of the PHEVs monitored is presented with a vertical segment and a marker at the top; a text label reports the average number of charging events per 1000 km. Interestingly, the best in class (*Hydra)* appears to keep its FC low by applying very frequent charging events (49 charges / 1000 km) of limited depth (just above 2kWh per charge). Conversely, *Grus* appears to receive energy very rarely (1 charge / 1000 km) but through deep charging events (close to 10kWh per charge). It is important to point out that the grid energy into the battery parameter used for this analysis does not include the charging losses [19] and only reflects the increase in the internal battery energy, therefore the EC is meant at battery-level. To obtain the EC at grid-level, the OBFCM grid energy into the battery would have to be divided by the charging efficiency. The latter depends on the vehicle model and the charging methodology (through the domestic charger or public charging stations), but it can be assumed to be between 83 and 90 %, range that reflects the average efficiency of the on-board charger [37] when using Alternated Current (AC) i.e. the most adopted charging on PHEVs [38,39].

3.3.2. Real-world energy performance

The presented previously results suggest that the interdependency between FC and EC can be quite well captured by a linear correlation. Such a correlation enables to calculate with reasonable accuracy the fuel and energy consumption that PHEVs would obtain under any charging scheme and resulting real-world UF. This concept has been applied at individual vehicle level, as shown in Fig. 8, using the real-world FC and EC in different distance bins of their lifetime to obtain the linear correlation. The two points where the regression line crosses the x and y axes represent the indicative Pure Electric (PE) EC and the charge sustaining (CS) FC, respectively. Such a methodology can be used to separate the two different operating modes, even on vehicles that are used predominantly in one of these two, and characterise their consumption figures based on a set of real-world distance bins sourcing from normal usage monitoring. The results from corporate (company) and non-corporate (private) users have been aggregated together (see Table 4). Results show that both the CS FC and the PE EC obtained for corporate users are higher than the same values obtained for non-corporate ones, by +17 % and +48 % respectively. In principle, these values are independent from the UF and i.e. from the charging pattern applied by the user, meaning that the extra FC and EC are to be attributed to a higher energy demand at vehicle-level. The two groups match each other quite closely in terms of vehicle size: *Aries* is an SUV of small dimension (SUV-C), the remaining ones all belong to the Standard-C segment and can be identified as hatchback or crossover vehicles, data comparability is therefore ensured. The CS FC results are in line with the figures that are obtained by similar vehicles without external charging capability (charge sustaining HEVs, see Fig. 4). Likewise, the PE EC

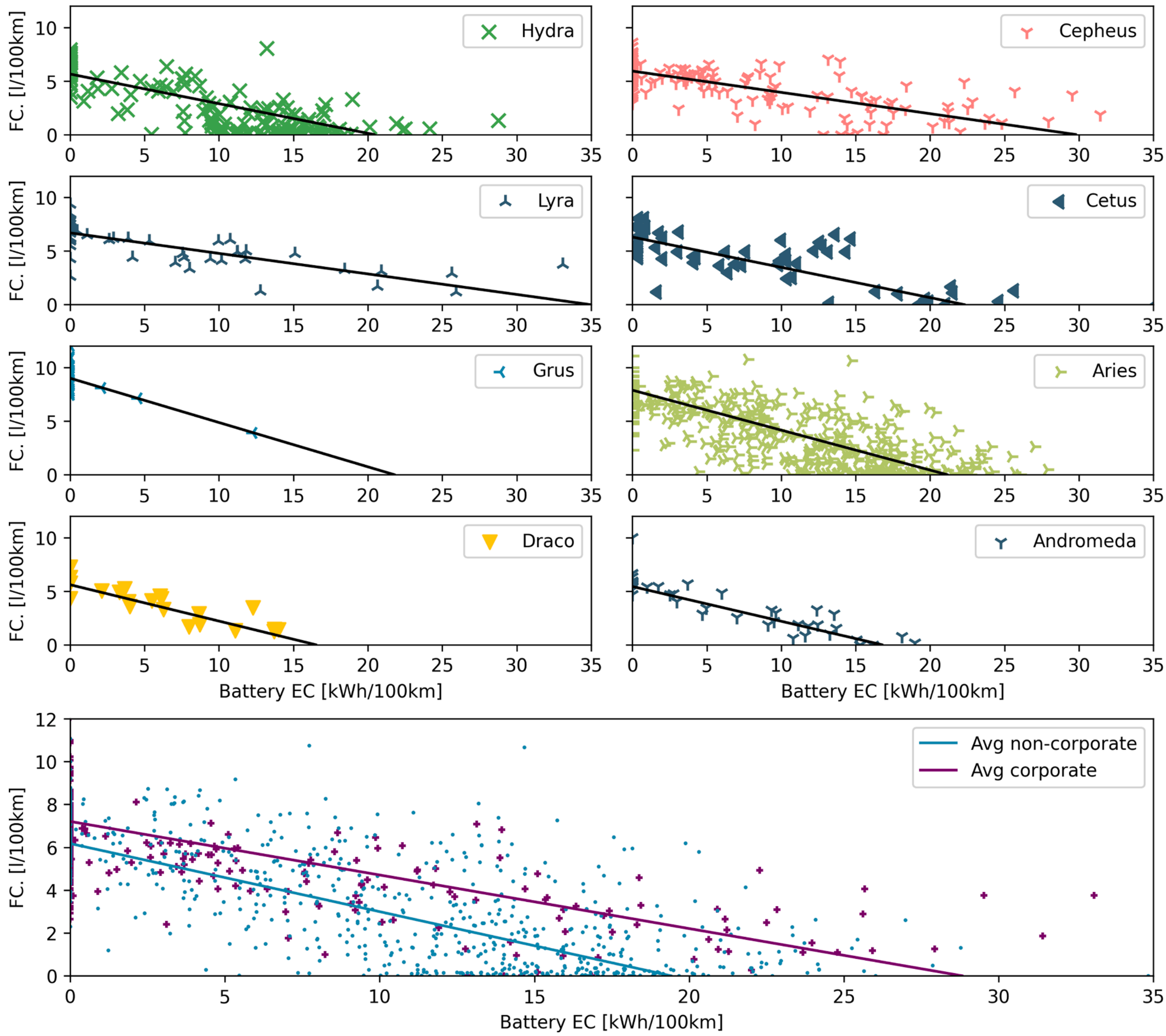

Fig. 8. PHEVs real-world performance analysis according to the different operating modes (charge sustaining and pure electric) and comparison between corporate and non-corporate users.

Table 4
PHEVs pure electric and charge sustaining performance extrapolated from real-world data per user type (corporate or non-corporate).

User type	Vehicle name	Average speed [km/h]	PE EC RW [kWh/100 km]	CS FC RW [l/100 km]
Corporate	Cepheus	62.92	29.76	5.92
	Grus	33.43	21.76	9.00
	Lyra	51.99	34.91	6.69
	All	**49.45**	**28.81**	**7.21**
Non-corporate	Andromeda	58.03	16.99	5.29
	Aries	46.81	21.13	7.89
	Cetus	45.91	22.28	6.30
	Draco	61.78	16.49	5.60
	Hydra	25.95	20.40	5.64
	All	**47.70**	**19.46**	**6.15**

values here presented, which are within the range of 16–30 kWh/100 km, are of the same order of magnitude as the figures regarding BEVs presented by TNO [39]. Anyhow, the results here presented would have to be first adjusted for charging losses to enable a direct comparison.

From the higher PE and CS consumption in corporate PHEVs in our sample, one could assume that these vehicles do not consume more fuel only as a consequence of a reduced charging (i.e. UF), but also because of a more energy consuming driving, either because of a less efficient driving style or an increased energy request for auxiliaries (cabin heating or cooling) [40]. Anyhow, to draw robust conclusions on this aspect, a larger sample would have to be captured. The precise source of the difference could be further investigated in a follow-up study based on the same dataset, by analysing the timeseries from the trips rather than the trip aggregated data only.

3.3.3. Utility factor discrepancy

Many concerns have raised regarding the discrepancy between PHEV type-approval and real-world CO_2 emissions [22,41]. The update of the utility factor (UF) curve was decided to alleviate the problem [16], assigning a statistical lifetime weight to the CS and CD emissions obtained in the laboratory. The data collected were used to derive for each vehicle technology the real-world average cumulative probability distribution of driven distance, a proxy to the UF used for weighing PHEV emissions, as presented in Fig. 9.

The UF concept encompasses two sub-concepts: (a) the distance driven in a day and (b) the assumption that on that given day the PHEV

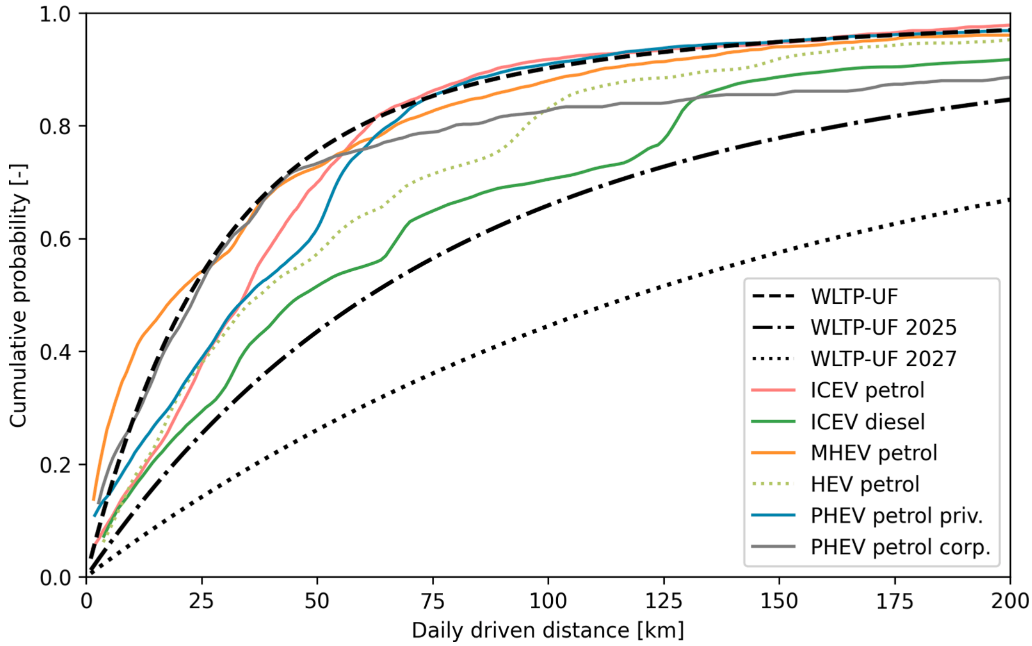

Fig. 9. Daily driven distance per vehicle technology (ICEV, MHEV, HEV, PHEV), fuel type (petrol and diesel) and user type (private and corporate-users, only for PHEVs). The WLTP Utility Factor curve, derived from the annual average driven distance from the European drivers, is also displayed as a reference in black lines (dashed → current UF curve, dash-dotted → 2025 UF revision, dotted → 2027 UF revision).

is going to drive electrically for as much distance as the WLTP-certified electric range. Regarding (a), this consists of a cumulative probability distribution of driven distance per day obtained from real-world data according to the mobility needs of citizens; this is what gives the shape to the UF curve (presented in Fig. 9 as "WLTP-UF"). From this distribution, it is possible to obtain the cumulative probability P of driving in a day less than a certain distance, e.g. the probability that a car drives less than 100 km in a day is 90 %. Regarding (b), this assumption was taken to link the daily driven distance to the lifetime CD distance. If a PHEV with an electric range of 100 km is considered, by starting every day with a fully charged battery the probability that a distance lower than the electric range is driven is 90 %, and therefore the chances that the distance driven on the same day is going to be in CD mode. Being valid for any given day, this is valid by definition for the whole vehicle lifetime, i.e. a PHEV with an electric range of 100 km will finally drive 90 % CD and 10 % CS. These results are valid as long as both (a) and (b) are fulfilled, something that is not always reflected in real-world operation.

Apart from diesel ICEVs and petrol HEV, that in any case are out of scope for the UF curve, a good matching is observed between the WLTP-UF and the real-world distributions, something that was confirmed also in a study by Paffumi et al. [42]. This finding hints that the PHEVs FC problem is to be attributed to factor (b) more than factor (a), and therefore to the assumptions that (1) PHEVs receive one full charge per night and (2) a distance equal to the certified electric range is going to be driven in charge depleting (i.e. with very low FC). Both assumptions appear to be optimistic, at least for the vehicle sample investigated in this study. As presented previously, no PHEV was charged to an extent that would satisfy the one charge per day requirement. In addition assumption (2) is not confirmed due to additional real-world consumptions originating from auxiliaries and other factors that prevent reaching the full CD distance of the certification test. Finally, vehicle and battery ageing can also contribute to the PHEVs FC problem, calling for a careful analysis of the factors at play as carried out by Pavlovic et al. [43]. The study explains how the battery capacity drop can be to some extent compensated by an improved vehicle efficiency because of reduced drivetrain losses, and that deeper investigation and large scale data are still missing to have a full understanding of this topic. As time passes and more data is collected, possibly also the project behind this study will be able to contribute to research in the ageing field.

In 2025 and 2027, revised coefficients for the UF are applied in the EU certification (see Fig. 9). This will cause the assumption on the CD distance share to drop significantly, and the FC and CO_2 emissions calculated at type-approval will increase by a factor of more than 2 in the first revision (2025) and 3 in the second (2027), as shown in Fig. 10. As a result, despite PHEVs may offer significant tailpipe CO_2 emissions reductions (unmatched by other technologies), they could be seen in the future as overly expensive vehicles without corresponding emissions benefits. This could hinder their adoption as a bridge to zero-emission transport [44]. To ensure that PHEVs bring the expected benefit to the environment, their usage must prioritize electric driving. Schemes like minimum charging requirements could help make PHEVs a truly valuable sustainable choice.

3.4. Driving and ambient conditions

3.4.1. Urban, rural and motorway shares

The data collected allow an in-depth view on speed and driving condition distributions. The urban, rural and motorway distance shares were calculated for each trip according to EU Regulation 2016/646 [45] that defines them based on these instantaneous vehicle speed conditions: in between 0 and 60 km/h for urban, 60 and 90 km/h for rural and above 90 km/h for motorway.

Comparing the trip distance with the driving conditions shares we get the trends in the left subplot of Fig. 11, with urban being the predominant driving condition for low distance trips (below 25 km), motorway for high distance trips (above 70 km), and rural covering whatever remains and peaking for intermediate distance trips (between 25 and 70 km). In the right subplot the lifetime motorway share is compared with the annual distance from each vehicle. Vehicles that accumulate more km in a year have a higher share of motorway driving. The regression formulas are provided in Appendix C.

The ternary plots in Fig. 12 present the impact on FC of the driving condition, urban, rural or motorway, for each powertrain technology. The different hexagons represent a different mix of the aforementioned conditions (e.g. the top corner represents 0 % urban, 0 % rural and 100

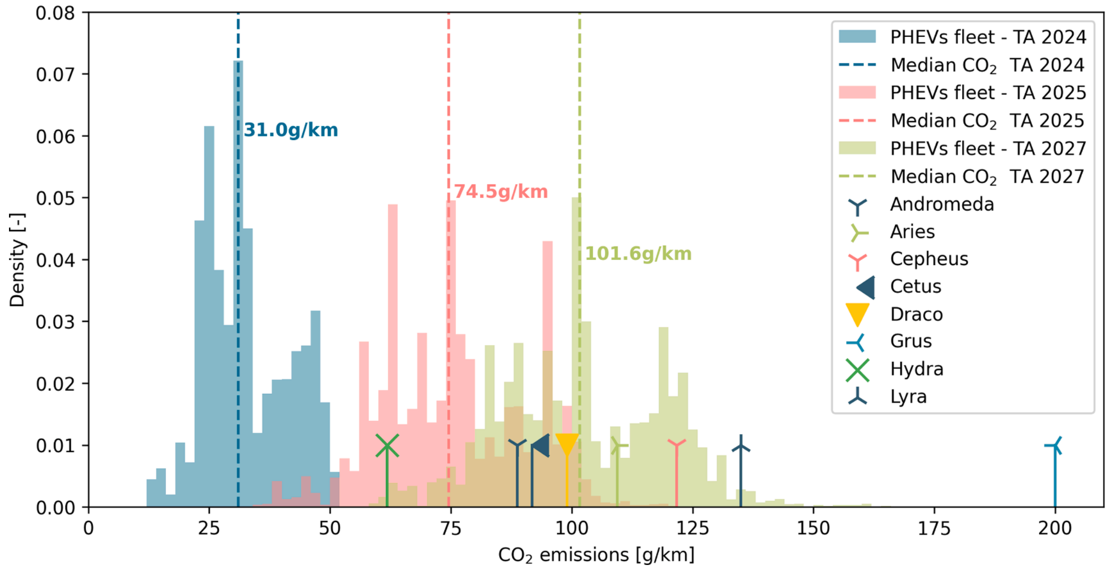

Fig. 10. Projection of the CO_2 emissions distribution from the fleet of PHEVs with the 2025 and 2027 UF revision (using 2022 PHEVs registrations from CO_2 monitoring).

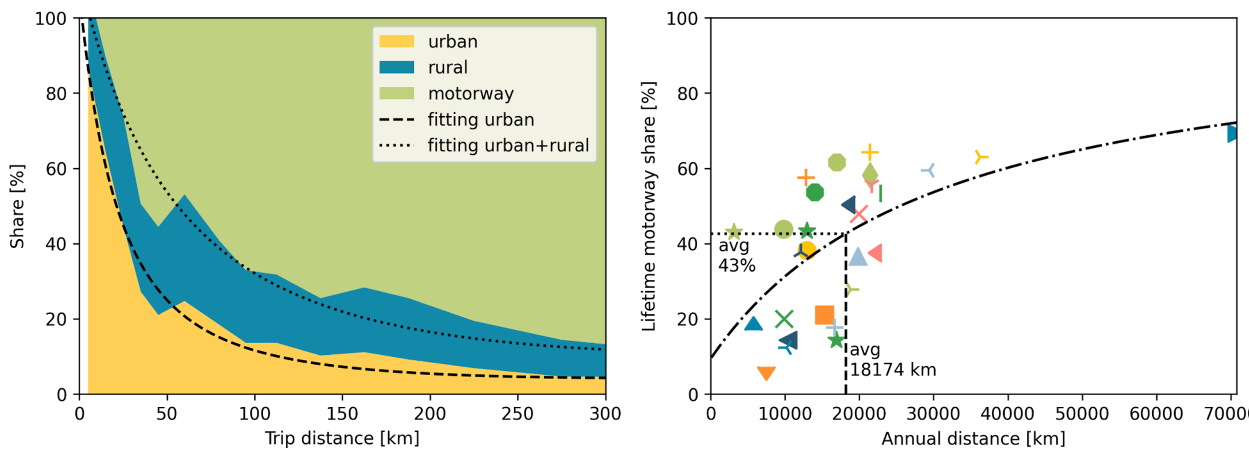

Fig. 11. In the left subplot, urban, rural and motorway distance shares per trip and regression lines to generalise patterns. In the right subplot, the dependency of the lifetime motorway share from the annual distance driven by the vehicle.

% motorway) and are coloured according to the change in FC with respect to the average FC. It is to be highlighted that a wider range was used for PHEVs to reflect their characteristics, i.e. a more pronounced FC variability because of the alternated charge-depleting and charge-sustaining operation. Similar FC impact grids are obtained for ICEVs and MHEVs, justified by the similarities in these powertrains, with the lowest FC obtained under rural conditions (blue shaded parts of the grid in the bottom right corner of each ternary plot) where the delta FC can be as low as −2 l/100 km. The highest FC impact is obtained for high shares of urban driving (red shaded parts of the grid), where the delta FC can be as high as +1.20 l/100 km. Finally, no FC impact is obtained for motorway driving (green shaded parts of the grid), hinting to fact that the FC of these vehicles is optimised for this condition which is very energy demanding. The situation is less clear for HEVs where colour shades appear more mixed up in the grid, possibly because of the more limited amount of data not enabling to neutralise the FC experimental noise, or as a consequence of the less predictable energy management and the battery SoC fluctuations [46]. Anyhow, trends can still be identified, with rural driving appearing marginally better than urban driving. Conversely from ICEVs and MHEVs, HEVs are mostly affected in motorway driving with the FC delta as high as +1.26 l/100 km. Urban driving, which is the condition mostly affecting ICEVs and MHEVs, doesn't appear to be as much penalising on this other more electrified powertrain, likely because of the higher braking energy recuperation mitigating the FC increase due to frequent accelerations and braking events [47]. Anyhow, the comparison between urban and rural cannot be fully conclusive as no clear picture is returned.

Regarding PHEVs, the analysis highlighted that no significant difference exists between private and corporate users for what regards the impact of driving conditions, hence the PHEVs sub-categories are being considered altogether. Urban and rural appear equally favourable to FC with negative delta values; anyhow, this result can be mostly due to the larger share of charge depleting operation and would have to be discussed separately. Motorway is what clearly brings the worst impact, with the FC delta as high as +3.85 l/100 km. This is due to the high energy demand associated with motorway speeds and the fast depletion of the energy stored in the battery; this inevitably causes the activation of the engine, especially for long distance trips, from which we can conclude that limiting speed can bring significant benefits for PHEVs.

3.4.2. *Ambient temperature impact*

Vehicles that were monitored over different ambient temperature

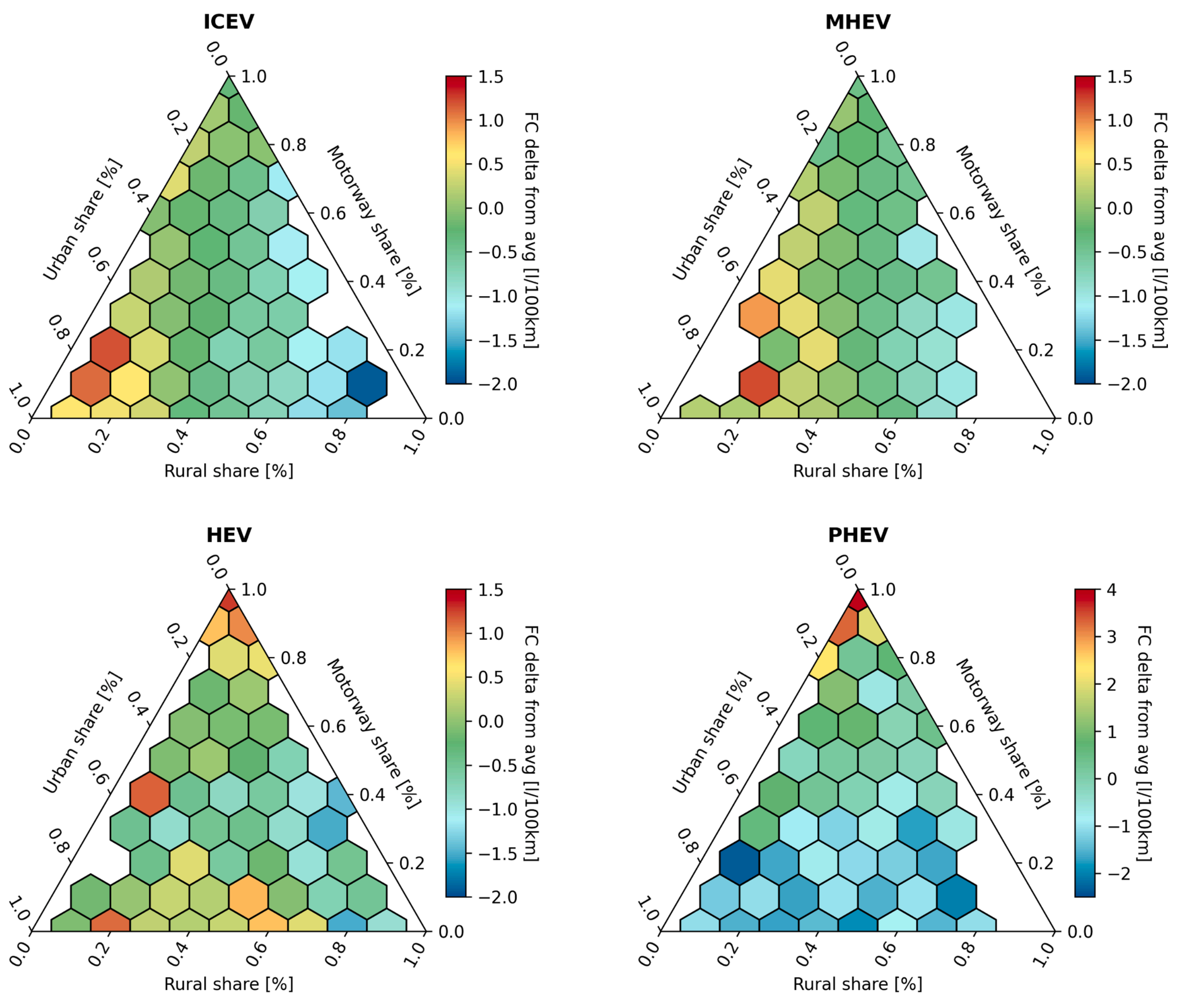

Fig. 12. Impact on fuel consumption of urban, rural and motorway driving shares with respect to the average fuel consumption for each vehicle technology (ICEV, HEV, MHEV, PHEV).

conditions were selected for quantifying the impact of ambient conditions on FC. The average FC was obtained per vehicle technology and fuel, separating petrol and diesel vehicles, to account for the different engine thermal inertia. The sample was split into five different temperature bins ranging from −5 to 40 °C, as shown in Fig. 13. The increase in FC was then obtained comparing to minimum fuel consumption bin and by computing the simple average of the increments in relative terms. The result is therefore not weighted according to trip distance, and this highlights the impact of ambient temperature in short trips, that is otherwise mitigated for longer trips. PHEV petrol corporate could not be analysed due to lack of data over the different seasons.

For all technologies, except for petrol HEVs, the same trends are identified and reflect the temperature impact obtained in other studies [48,49]. The FC is minimised in the ambient temperatures bin 15–20 °C, and increases both for colder and warmer temperatures. Cold temperatures affect FC for multiple reasons: higher frictions due to oil viscosity [50,51], longer warm-up for vehicle components [52], reduced engine start and stop [53,54], higher vehicle air drag for increased air density [55]. On the other hand, warm temperatures affect FC because of: increased usage of air conditioning and higher rolling resistance from tires [56]. Starting with the cold temperatures bins, it can be noted that ICEVs and MHEVs are impacted in a very similar way (diesel ICEVs less than petrol ICEVs), with limited impact in the 7.5 to 15 °C bin and a more pronounced impact in the −5 to 7.5 °C, but with lower slopes in the connecting segments. Highly electrified vehicles, HEVs and PHEVs, are much more affected in terms of FC increase in cold temperatures, and this is likely justified by cabin heating [57]. On HEVs, the engine is activated more frequently to make waste heat available for the cabin. On PHEVs, that can be operated in a very similar way to pure electric vehicles, with respect to cabin thermal management, electrical energy might be used in electrical heaters effectively increasing energy consumption [48], reducing range and causing higher fuel consumption because of depleting the battery sooner in a trip. Looking at warm temperatures, we see that a low FC impact is obtained in the 15 to 22.5 °C bin. This can be explained by the way thermal comfort can be obtained within the cabin, since effective cooling can be achieved by simply opening the windows therefore requiring no extra auxiliaries to operate. For the warmer temperature bin 27.5–40 °C though extensive use of the air conditioning is expected, and the FC impact for ICEVs, MHEVs and PHEVs increases more than proportionally compared to the previous temperature bin.

The only technology that challenges the arguments above is petrol HEVs, which actually seem to perform at their best in warm temperatures. Finding a reason without entering detailed analysis is challenging, and this is maybe to be found in the efficiency at low temperatures, which are causing a very significant FC increase for this technology (the

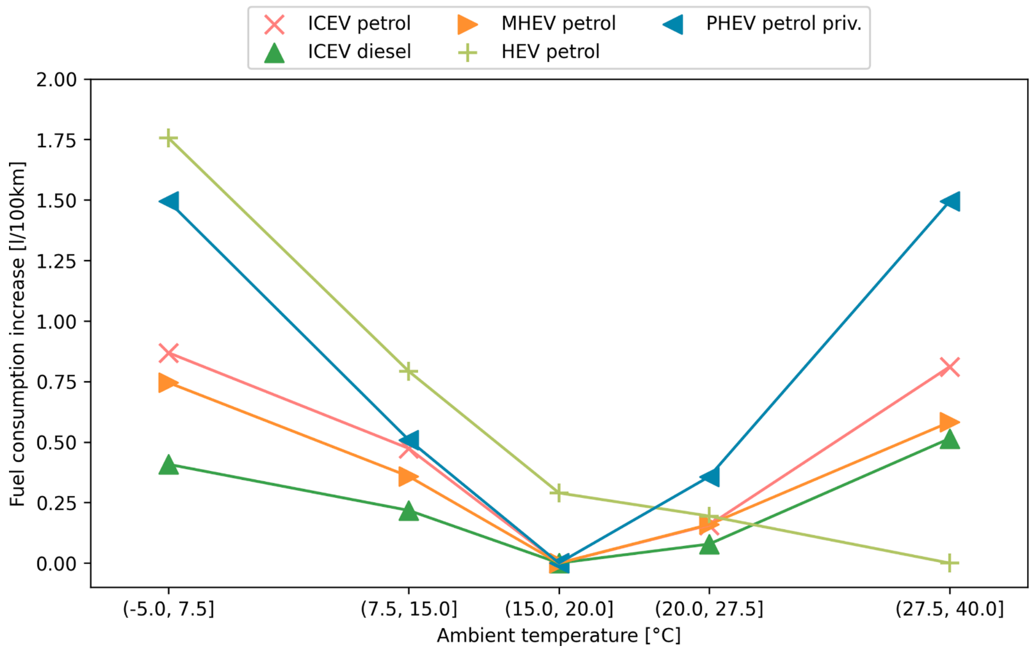

Fig. 13. Fuel consumption increase due to ambient temperature for different vehicle technologies.

highest FC increase in the conditions under consideration). Because of the way this technology operates, with very frequent engine starts and stops to optimise fuel consumption, it might be that the engine cold-start at cold temperatures has a much bigger impact, effectively off-setting the whole temperature analysis in comparison to other technologies.

4. Conclusions

OBFCM data are key for understanding road vehicle performance in real-world operation. The analyses and results presented in this study aim to provide insight for the interpretation of the fleet-wide OBFCM monitoring dataset published by the EU. This study adopted an innovative approach to collect fuel and energy consumption values from road vehicles and characterise the real-world operation.

A number of vehicles (50) with different powertrain technologies, usage conditions and from different regions in Europe were monitored during their real-world operation, generating a dataset of fuel and energy consumption data enriched by vehicle telemetry to explain the variability (aggregated data is made publicly available). From the analysis of our sample, urban conditions increase fuel consumption up to 1.2 l/100 km on ICEVs and MHEVs. Motorway conditions increase fuel consumption by 1.26 and 3.85 l/100 km on HEVs and PHEVs, respectively. Ambient temperature also affects fuel consumption, with extreme temperatures causing an increase of up to 1 l/100 km for ICEVs and MHEVs, and of 1.5 l/100 km and more for HEVs and PHEVs.

PHEVs fuel and energy consumption were analysed separately, using an innovative methodology supported by the richness of the collected data that enables to look both into the driving and the charging of these vehicles. Separate values for charge-sustaining and pure electric consumption were inferred from the data, also highlighting an increased fuel and electric energy consumption in the PHEVs from corporate users in our sample. The interplay between the charging and the real-world average fuel consumption was also discussed. The reason for the discrepancy between certification and real-world data as high as +350 % [3] is to be found, firstly, in the limited charging and, secondly, in the lab-to-real-world differences causing an increase in the energy consumption, something that exists also on other technologies, but that is magnified in this specific one due to the coexistence of the thermal and electrical powertrains. The gap cannot be explained by PHEVs being driven differently in the real-world: from the evidence generated in our campaign, they are used in a very similar way than any other vehicle technology. Anyhow, noticeable differences in the fuel and energy consumption were identified between private and corporate PHEV users in our sample, with the latter requiring +17 % more fuel and +48 % more electric energy.

With a view to future research, similar data collection campaigns can provide useful feedback for analysing the progress made on road transport decarbonisation, and when combined with the official OBFCM monitoring dataset enable a deeper understanding of the road vehicle fleet energy consumption. OBFCM and telemetry data is necessary for filling in the current knowledge gaps existing for those vehicle technologies where extensive in-use literature is missing, e.g. pure electric or fuel cell electric vehicles [58–60]. The power of OBFCM systems could be further increased by including additional relevant information such as battery parameters for externally chargeable vehicles (PHEVs and EVs) like the state of charge and power output, the usage of auxiliaries, the external conditions (ambient conditions but also traffic conditions). Long-term monitoring of vehicles circulating in the fleet could also fill the knowledge gap for what regards the longevity of components under real-world conditions, e.g. to determine the actual loss of battery capacity due to ageing in batteries of PHEVs and EVs, and give a clear indication on the performance degradation over time [61,62]. Similarly, it provides an accurate and effective solution for the benchmarking of energy savings from technologies that cannot be easily characterised by laboratory tests, and that can only be characterised through the collection of a sufficient quantity of real-world data, e.g. Vehicle Integrated PhotoVoltaics (VIPV) [63], advanced energy management strategies [44], Vehicle-to-everything (V2X) energy optimisation strategies [64], efficient mobile air-conditioning systems [49] and others.

The results presented in this study were derived almost exclusively from the analysis of trips aggregated data (e.g. distance, fuel, mean speed, average ambient temperature, and other statistics). This study consists of a first high-level analysis and dive into the exploitation of the collected data, which comes with limitations on the number and depth of insights that can be drawn. A higher potential lays within the dataset, which can be untapped by carrying out in-depth analysis of the timeseries signals, by fetching more data from other available sources (e.g. traffic, weather or geographic information systems), by capturing a higher number of vehicles or by solving issues in the infrastructure and improving the monitoring of the relevant driving conditions. These could be targets for a follow-up analysis that seeks to exploit to a larger degree what OBFCM and telemetry offer.

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CRediT authorship contribution statement

Alessandro Tansini: Writing – original draft, Validation, Methodology, Formal analysis, Data curation, Conceptualization. **Andres L. Marin:** Writing – review & editing, Validation, Software, Methodology, Data curation. **Jaime Suarez:** Writing – review & editing, Validation, Methodology, Data curation. **Nestor F. Aguirre:** Visualization, Software, Data curation. **Georgios Fontaras:** Writing – review & editing, Supervision, Methodology, Investigation, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A

Table A1
Vehicles from the real-world collection campaign. more data available at https://code.europa.eu/jrc-legent/legent-data within the JRCMATICS collection. Vehicle matching to be carried out through the vehicle ID field.

Name	Type	Fueltype	Car segment [11]	Usertype	Vehicle ID
Andromeda	PHEV	petrol	Standard-C	test	dc25adc923b11f5d94b09cc220b557e26a89016e
Antlia	ICEV	diesel	Standard-M	private	83257e070e707569f7199e81fd40e768af201983
Apus	ICEV	diesel	Standard-M	private	13f2820d8f939e9ce81c13ee61cb11c8bbc815eb
Aquila	PHEV	petrol	SUV-C	private	e67a57bc2d09f31c723751d850ced4211b61a451
Ara	ICEV	diesel	SUV-J	private	eeb552f32be0c916424a55b23592d88ecff536b8
Aries	PHEV	petrol	SUV-C	private	735269c8c8a7531fbc97da8983d81fb512591f8d
Auriga	ICEV	petrol	Standard-C	rental	04559678fc88b41added54c29c1a2156adb4a5a3
Caelum	HEV	petrol	SUV-B	private	937293928580281a8caf8f3c66113eb7c1e4f6b4
Cancer	PHEV	petrol	SUV-C	test	8628266b29e2388005d1870406cc1056c0804d11
Carina	MHEV	petrol	Standard-C	private	16ea5ba6837576eaaa7fa0665a45386834dcb74e
Cassiopeia	MHEV	petrol	Standard-C	private	576eb7590f41a12502d36ea3d603a61f908968a3
Cepheus	PHEV	petrol	Standard-C	corporate	9932239c9c2a8579b9f8903864d876ae99512a10
Cetus	PHEV	petrol	SUV-C	private	99f8c0dfd02b3647385ac6c8afdbe1cfece94228
Circinus	ICEV	petrol	SUV-B	rental	b0955b3360789b8f5f5a5493137428baeeaf93b1
Columba	ICEV	petrol	Standard-F	test	bc6280b7232644d94e5ce7b1fe1ff088e1dc7472
Crater	MHEV	petrol	Standard-F	test	1c31e55556aeae4f65bedfe711911d5bcba1f7c6
Cygnus	ICEV	petrol	SUV-B	rental	b9f0eca7cf72583fb0702dcc9a1207d49765767c
Draco	PHEV	petrol	Standard-C	test	35900965c9a886724182a6ab55437abfbc4a44de
Eridanus	ICEV	diesel	SUV-C	corporate	9b56d66d4cf2158314bb510e15b308b68c1a7d4d
Fornax	ICEV	diesel	SUV-J	test	da95c40a5cf6a391e7fe9659aa88332eca4c5588
Grus	PHEV	petrol	Standard-C	corporate	aaa2165f3cedbc9a855699f7f06ed9b8cc2ead5e
Horologium	ICEV	diesel	Standard-C	corporate	665c327dc8a1ddbb53a21ec52f497e1764d98112
Hydra	PHEV	petrol	Standard-C	private	9e1fc0e34f35326b3f99e42f45844631420218fa
Hydrus	ICEV	petrol	SUV-J	private	505a81bbe9270e2ac8345a984c0a6ba366193ee9
Indus	ICEV	petrol	SUV-C	private	6a21eac7c858f55b8dfb2e108351cbae92f804d6
Lacerta	ICEV	diesel	SUV-C	rental	fb1755d22d646f0be54fed8595cdacdf60b15f13
Lepus	ICEV	petrol	SUV-J	private	436f5c2a3305cdc7a7351ce2615bbeaf4f119d2f
Libra	ICEV	diesel	Standard-C	private	3384da1d76d671a16ef74c9a1e994ad58afcc749
Lyra	PHEV	petrol	Standard-C	corporate	87138958e2b614179b8babb47ed185b29e2cae14
Monoceros	ICEV	diesel	SUV-C	private	d416c838d68479410348bd19ff93acc478a5e3f0
Musca	MHEV	petrol	Standard-A	rental	b4e4e2759a2960f2a9e96d28531a9e8c330f8b07
Norma	MHEV	petrol	Standard-B	private	fdf0100de0d81c4fac833421002113b7e4a90c31
Orion	MHEV	diesel	MPV-M	rental	4c08bf16a8e637400b9b24ca1d8832403aeb1b2e
Pavo	HEV	petrol	Standard-C	private	01f52de16e453da6caf09bbf3ffde3c3eb6c61e2
Pegasus	ICEV	petrol	SUV-J	rental	54629f8417923d1198e3f69ab0883e26bd9c7577
Perseus	PHEV	petrol	SUV-J	private	fb8a705c4195f1a7f0fafb8a89837d41f86d2a1c
Phoenix	MHEV	petrol	SUV-B	test	6ce7d3d1084667ac977137b4547116e3e219a8ff
Pictor	HEV	petrol	SUV-B	private	f0e3023e66e246172bf611901c40f6bb4807d14c
Puppis	ICEV	diesel	SUV-J	corporate	ff8b57acbeb4644fd6444bcb39b1a265fc8e87d5
Pyxis	MHEV	petrol	Standard-C	private	ce3f53cd501a80605f92940025de7aac5ab1ed81
Sagitta	HEV	petrol	SUV-J	private	e257b6a84e00844eb7faa119aa989e0f2f3e60f9
Sagittarius	MHEV	petrol	SUV-B	private	005a5cb9e3692d47ea362fecad5ce9b2432f6b06
Sculptor	HEV	petrol	Standard-C	private	883ed74a8a9cfdf250bfed6624cec5ab996bedbe
Serpens	ICEV	petrol	Standard-B	private	86be428c09b7a5ec46cde39ee4945e0c0bf82e96

(*continued on next page*)

Table A1 (*continued*)

Name	Type	Fueltype	Car segment [11]	Usertype	Vehicle ID
Taurus	ICEV	petrol	Standard-A	private	6e8cb27221a6ef8a60db8e48024f23df3945f24b
Tucana	MHEV	petrol	Standard-A	rental	15670b845504b303146a04e54154470d22ae3918
Vela	HEV	petrol	SUV-B	private	7f3e01100e23bc71c3a46241ebb9af88e552b98b
Virgo	ICEV	petrol	Standard-B	rental	863a4b0c0bfd85e5e4e7df1af4b065b45ff8b4e8
Volans	MHEV	petrol	Standard-C	private	9066e2ae374009be4f6ace10c642751f1b72c63b
Vulpecula	HEV	petrol	SUV-B	private	7b6d9177528ac441877598f1d9d0978a559e3b39

Appendix B

Transmission errors and data loss management

The OBD dongles collect data from the vehicle diagnostics and the internal GPS module, creating data packages that are transmitted over-the-air to our server. Transmission happens via UDP (User Datagram Protocol). The package format follows the Traccar protocol, requiring each package to terminate with a checksum. If the checksum computed at the server side does not match with the one transmitted by the OBD dongle, or if the format of the package is unexpected, the package is dropped. Otherwise, the package is processed normally by the server and its data is stored. This approach ensures that transmission errors do not affect the captured data by introducing outliers.

For what regards data loss, the OBD dongles can handle situations of missing connectivity through storing the data temporarily in an internal buffer. The buffer is purged as soon as the connectivity is restored. Data is retained for up to 5 min of missing connectivity, i.e. the time required to fill up the buffer. When the buffer saturates, new data bundles start overwriting older data bundles, effectively causing data loss when the missing connectivity condition is prolonged. Data analysis revealed that this situation is not encountered frequently, showing how the 5 min buffer is effective for most of the missing network conditions and how the data loss issue doesn't affect significantly the overall results presented in this study. Anyhow, trips where the share of missing data exceeded the 20 % have been excluded from the analysis.

Appendix C

Equations from fitting lines in Fig. 11.

Driving condition share versus trip distance.

$\exp(a \bullet x) + \frac{b}{(x+c)^2}$ with.

- urban: a = -3.04198572e-03, b = 2.15863786e +05, c = 4.51810334e +01
- urban +rural: a = -4.44669896e-03, b = 1.36265165e +06, c = 1.11208819e +02

Lifetime motorway share versus annual distance

$100 - \frac{a}{x+b}$ with a = 2845919.47, b = 31413.27.

Data availability

Data presented in section 2.3 can be found at https://code.europa.eu/jrc-legent/legent-data within the JRCMATICS collection. This collection includes trips aggregated data and vehicles data. The repository is updated once per month to include newly collected data. For the purpose of this study, only data collected until end of October 2024 were used. Authors kindly ask future users of the dataset to cite the present paper as reference when using the data.

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