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Evaluation of plug-in hybrid vehicles in real-world conditions by simulation

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A R T I C L E I N F O

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A B S T R A C T

Assessing the real-world energy performance and emissions of Plug-in Hybrid Vehicles (PHEVs) is complex: it depends on their usage (trip distance, recharging behavior), and results in different combined uses of their thermal and electric propulsion.

In this study, vehicle simulators were calibrated using experimental data (in-lab and on-road), allowing a comprehensive range of uses spanning vehicle configurations, battery capacity, outside temperature and driving profiles. These results were synthetized through a method weighting each simulated use-case according to their probability, based on statistics of daily distance travelled and temperature. The assessment was made for a wide range of battery capacity and recharging frequency, and provided the real-world share of electric drive, CO_2 emissions, fuel and electricity consumptions of PHEVs according to these two key parameters. Finally, in a very likely battery-constrained environment, PHEVs should be fostered to minimize GHG emissions providing that they are recharged at least every-five driving days.

1. Introduction

1.1. Context

Transport related greenhouse gases (GHG) emissions represent approximately a quarter of total EU GHG emissions (EEA, 2021). In the context of targeting carbon neutrality in 2050 as set by the EU Green Deal (European Commission, 2019), reducing transport

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related GHG emissions represents both an important stake and challenge. The present study focuses on passenger cars only. When considering each vehicle individually, there are several ways to consider their GHG emissions:

- The Tank-to-Wheels (TtW) approach focuses only on the tailpipe emissions;
- The Well-to-Wheels (WtW) approach is more complete and considers the GHG emissions related to the production of the energy carriers;
- The Life Cycle Assessment (LCA) approach is holistic and also considers the GHG emissions related to the production of capital goods that are necessary to the transport system (e.g. vehicles, infrastructures of the energy system, etc.).

Obviously, the LCA approach is the most satisfying one as it is the most relevant to climate related issues. Nevertheless, the TtW and WtW approaches should also be considered simultaneously because they are currently regulated in Europe (TtW for the vehicles (European Parliament, 2019); WtT with combustion for the fuels according to the renewable energy directive – RED (European Parliament, 2018)). For example, a solution that would have a high performance in the LCA scope, but a bad performance in the TtW scope would probably face big barriers to its development in the EU market.

In this context, Plug-in Hybrid Electric Vehicles (PHEVs) represent an interesting option as they seem to address the challenges with low GHG emissions at each stage (TtW, WtW and LCA) (IFPEN, 2018). Furthermore, they can relieve some of the (time) pressure on the implementation of fast charging infrastructures for Battery Electric Vehicles (BEVs) so as to make their rollout feasible in a shorter timeframe. However, it is believed that the assessments currently available in the literature may require some updates:

- TtW: the OEMs are committed to reducing the TtW CO_2 emissions of passenger cars (in gCO_2/km) by 37.5 % in 2030 compared to a 2021 starting point (European Parliament, 2019). A 55 % reduction compared to 1990 levels is proposed in the fit-for-55 package (European Parliament, 2022). It is highly likely that, to reach this target, a high amount of electrification will be necessary, including PHEVs as they generally give CO_2 emissions in the range of $\sim$ 30 gCO_2/km. As of today, these TtW CO_2 emissions are assessed based on the Worldwide Harmonized Light Vehicles Test Procedure (WLTP). The WLTP does not necessarily consider the real-world emissions of the vehicle, which could affect PHEV credibility in the future for at least the three following reasons:

1. Some PHEVs are purchased due to tax incentives but are rarely plugged in (especially company cars) (ICCT, 2020).
2. Some journeys are much longer than the WLTC over which the CO_2 emissions are assessed. Therefore, it is possible that in some cases, the Internal Combustion Engine (ICE) runs for a larger proportion of the total distance travelled than expected in the regulation. According to German statistical studies (Infras, DLR, IVT und infras360, 2018), only 2 % of daily trips are longer than 100 km, but they account for 26 % of the mileage driven. Similarly, in France, only 1.3 % of the trips are longer than 80 km, but account for 40 % of the total mileage (approximatively. 6000 km/y), including around 50 % of them travelled by car (La Revue du CGDD, 2010). Therefore, these "rare but long trips" may have a significant impact on the real-world fuel consumption and TtW emissions of PHEVs, which should be assessed properly.
3. The PHEV has a higher weight than a conventional HEV or pure ICE vehicle – a downside for fuel consumption and CO_2 emissions if not charged.

- WtW and LCA: several WtW and LCA studies, such as those led by Ricardo (Ricardo, 2020) or by IFPEN (IFPEN, 2018; IFPEN, 2019), rank the PHEV among the best solutions in terms of CO_2 emissions. This is especially true if they use renewable fuels. In some very favorable cases, PHEVs can even have lower CO_2 emissions than BEVs over their life cycle as their battery is smaller – this will of course be highly dependent on the driver's behavior in charging the vehicle as well as the carbon intensity of the energy sources. If they have encouraging outcomes for PHEV, these studies do not answer the question of the real ratio of all-electric drive from PHEVs (raised above, also called "Utility Factor", UF), which may be a limiting factor to the applicability of their conclusions.
- Systemic aspects: more recently, Concawe developed optimal electrification scenarios of passenger cars, aiming at minimizing their WtW CO_2 emissions under constraints of battery availability (Shafiei et al., 2022). They concluded that, under limited battery availability, PHEVs are the preferred option before BEVs to minimize WtW CO_2 emissions of new passenger cars, even under quite conservative utility factors, ranging between 20 % and 50 %. This result is explained by the fact that, as long as the overall battery availability is limited, it is more efficient to electrify trips by spreading smaller batteries amongst many users who use their full capacity, than by allocating big batteries to few users who generally use only a small share of their full capacity on a daily basis. However, the question remains whether the real-world utility factors are beyond the 20 %-50 % threshold identified in this study.

1.2. Scope and objectives

If it is understood that PHEVs fueled by renewable fuels and low carbon electricity are an interesting option in terms of CO_2 emissions over their life cycle, this technical option also offers the opportunity to reduce the consumption of liquid fuels. This is particularly interesting in the frame of the outcomes of Concawe's work (Concawe, 2021), which mentions that liquid fuels for road transportation could be 100 % low-carbon by 2050, but with a consumption of liquid fuels that would be approximately-one third compared to today's level to be compliant with the GHG emissions trajectory designed by the European Commission in its 1.5 TECH scenario from "A Clean Planet For All" (European Commission, 2018). Hence, to make PHEVs fueled by renewable fuels a viable solution in the long term, they have to prove that they can compete with a third of the consumption of liquid fuels as a first approximation (and still comply with this in real-world operation).

In addition to CO_2 emissions and energy consumption, air quality is also an important factor for road transportation. PHEVs are often seen as an asset for air quality as they allow electric drive in the urban areas. However, the intermittent electric-drive of PHEVs (and hybrids in general) can present additional challenges for tailpipe emissions control due to multiple exhaust aftertreatment heating phases during a drive cycle – which are not necessarily well monitored in the current vehicle homologation process.

In this context, the aim of this study is to assess the energy performance and emissions of state-of-the-art PHEVs in real-world conditions. More specifically, this study intends to:

1. Assess life-cycle GHG emissions of PHEVs in real-world conditions, including their sensitivity to the behavior of the driver regarding recharging, to the battery capacity, to the trips distance, to the fuel used (e.g., fossil fuel vs low carbon renewable fuel) or to the carbon intensity of the electricity mix. This part of the study was built on experimental results detailed in other articles (Dauphin et al., 2022; Concawe, 2022) by using simulations. It is the objective of the present article to detail the method used for this and the results obtained.
2. Provide data on pollutant emissions of PHEVs in real-world conditions and determine if they are relevant solutions to preserve air quality and if the aftertreatment system efficiently manages the particularities of PHEV drive. For this purpose, an experimental campaign was carried out on a chassis dynamometer and on-road on two state-of-the-art PHEVs, and the test protocol focused on real-world driving emissions (RDE). This part of the study was used as input to the simulation work, and is detailed is other articles (Dauphin et al., 2022; Concawe, 2022).

In more detail, this article describes (Fig. 1):

- The experimental data, used as inputs to the calibration of the vehicle simulator – see paragraph 2.1;
- The calibration of a non-dimensional, physical vehicle simulator and its validation against experimental data (1) – see paragraph 2.2;
- The projection of the simulation results over a Design of Experiments (DoE) – see paragraph 3.1;
- The mathematical methods used to extract patterns from the simulation results database, allowing to obtain energy performance characteristics of PHEVs (CO_2 emissions, fuel and electricity consumptions, and Utility Factor – UF)) from any combination of usage

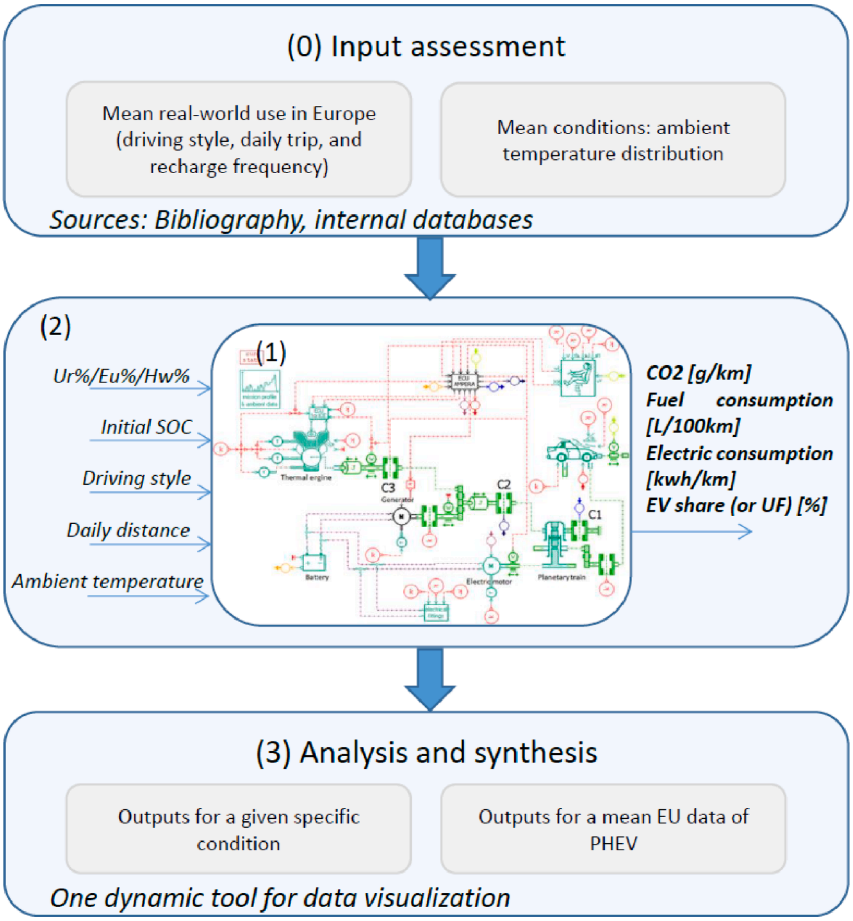

Fig. 1. Simulation workflow for PHEV energy performance real-world assessment.

parameters (initial State of Charge (SoC) of the battery, trip distance, driving style and profile (urban, extra-urban, highway) and ambient temperature) (2) – see paragraph 3.2;
- The statistical data representative of real-world usage, particularly in terms of Vehicle-Kilometers Travelled (VKT) and outside temperature (0) – see paragraph 4.2;
- Eventually, the forecasted energy performance of PHEVs over a real-world usage, as a function of its battery capacity and recharge frequency (3) – see paragraph 4.3;
- Subsequently, the results obtained in this study support the development of a vehicle life-cycle GHG emissions interactive platform – see paragraph 7 and Appendix F.

Furthermore, to facilitate the reading of this – quite long – article, the authors have made an extensive use of appendixes. They provide important details about the method used and the results obtained, however this article can be read and understood without referring to them.

2. Methods and data

2.1. Experimental data

It is not the purpose of this article to detail the experimental campaign performed in this study, and as mentioned above, it is detailed in other documents (Dauphin et al., 2022; Concawe, 2022). However, as the experimental data was used as input to elaborate and calibrate the simulations (which will be detailed in the next paragraphs), the necessary information is provided here for a good understanding of the approach.

Two PHEVs (Fig. 2) complying with Euro 6d standards were evaluated on a chassis-dyno (Fig. 3) and on-road (Fig. 4) using the same road profile, complying with RDE requirements (Fig. 5). The two vehicles differ only by their powertrain, one being diesel-fueled, and the other being gasoline-fueled (see Table 1 for main vehicles characteristics). The vehicles, a Mercedes C300de (Diesel) and a Mercedes C300e (gasoline), were tested under various conditions, including charge depleting and charge sustaining modes (i.e., tests respectively starting with a fully charged battery and a discharged battery), with various fuel compositions including traditional fossil-based fuels, 100 % renewable Hydrotreated Vegetable Oil (HVO) and 100 % renewable gasoline, blended with 20 % v/v ethanol (E20). Several chassis-dyno coefficients were used to assess the impact on performance of the weight difference between a PHEV and a Hybrid Electric Vehicle (HEV), having a lower-capacity battery. The set of measurements included fuel and electricity consumptions, CO_2 and regulated pollutant emissions (NOx, CO, HC, PN23, PM) as well as non-regulated pollutant emissions such as PN10, CH_4, NH_3 and N_2O.

It was observed a significantly higher fuel consumption on on-road tests than on chassis-dyno tests, although being driven on the same test-cycle. This discrepancy will be further discussed in the next paragraphs.

Overall, in addition to the generated experimental data, the experimental campaign allowed the direct comparison of:

- Diesel vs gasoline results: the test protocol includes a Diesel PHEV and a gasoline PHEV;
- Standard vs renewable fuels: the fuel matrix allows comparing a B7 with a 100 % renewable HVO; and the comparison between an E10 and a 100 % renewable gasoline, blended with 20 % v/v ethanol (E20);
- Full battery mode (charge depleting mode (CD)) vs empty battery (charge sustaining mode (CS));
- PHEV vs HEV: by artificially varying the weight of the vehicle on the chassis dyno (equivalent to the weight difference between a HEV and a PHEV), the test protocol allows a comparison of a PHEV with an equivalent non-rechargeable HEV.

2.2. Simulation platform set up

The simulations were carried out using Simcenter Amesim™ software. These models transcribe the physics of all devices present in conventional vehicles (combustion engine, transmission, etc.) and electric vehicles (battery, traction engine, power electronics etc.). The component performance maps are generated with automatic generation tools for the thermal engine, electric machine and battery, considering the detailed characteristics of these components.

A component dedicated to hybrid architectures (ECMS: Equivalent Consumption Minimization Strategy) was used to determine the optimal management strategy for internal combustion and electrical energy to minimize fuel consumption. It was calibrated to fit the

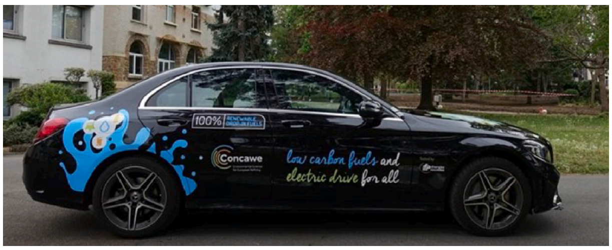

Fig. 2. Picture of the tested Mercedes C300de EQ Power.

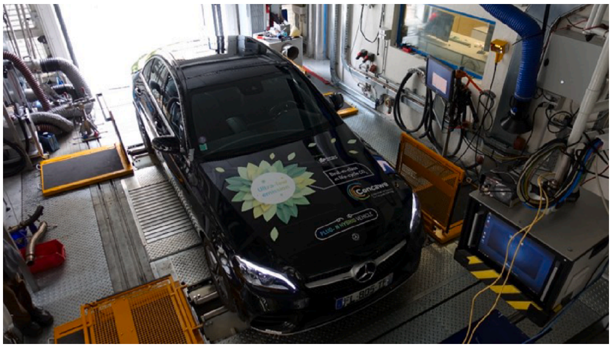

Fig. 3. Picture of the chassis dyno setup with one of the tested vehicles.

Fig. 4. Vehicle setup for on-road tests, with PEMS equipment.

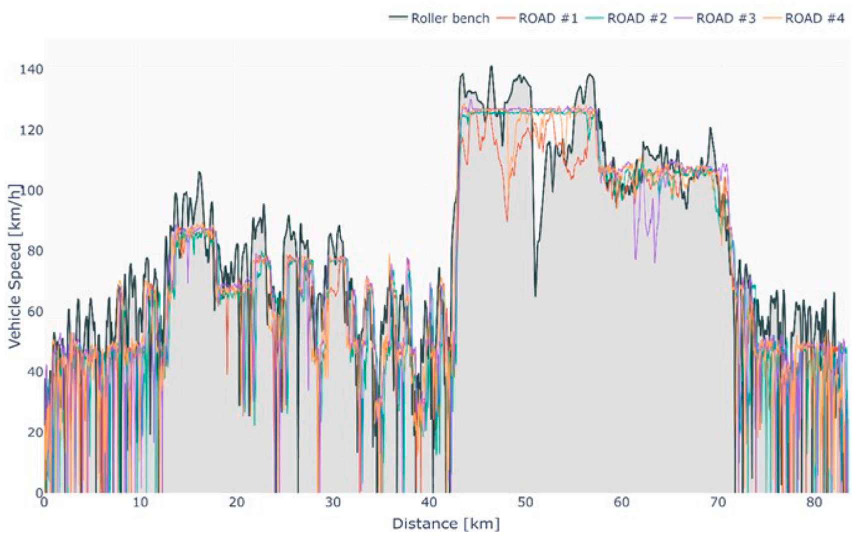

Fig. 5. Vehicle speed profiles (RDE compliant) measured during chassis dyno and on-road tests.

experimental behavior characterized in the previous chapter. Further details on these tools can be found in (Dabadie et al., 2017).

Further description about the simulation platform, its calibration and validation is provided in the appendix:

- Road laws (Appendix A);
- Simulation sketch and components calibration (Appendix B);
- Powertrain energy management laws (Appendix C);
- Simulator validation (Appendix D)

Table 1
Main specifications of selected vehicles. (1) In charge sustaining mode, i.e., empty battery at start of test. (2) Weighted between charge depleting mode (i.e. full battery at start of test) and charge sustaining mode, according to the current regulation.

	C300e EQ Power	C300de EQ Power
Regulation	Euro 6d-temp	
Fuel type	Gasoline	Diesel
Test mass [kg]	1885	1970
WLTP CO_2 [g/km]	CS (1): 146	CS: 140
	Weighted (2): 31	Weighted: 30.5
Thermal Engine	2.0L 4cyl 155 kW turbo Direct injection	2.0L 4cyl 143 kW turbo Direct injection
Transmission	9-speed automatic transmission	
Battery	13.5 kWh 365 V	
Electric motor	90 kW	
Hybridization	*P*2 parallel hybrid architecture	
Aftertreatment system	2*Three Way Catalyst (TWC) close coupled + Gasoline Particulate Filter (GPF) underfloor	Diesel Oxidation Catalyst (DOC) + Selective Catalyst Reduction Filter (SCRF) + Selective Catalyst Reductor (SCR) close coupled
Mileage [km]	4000	14,000

After calibration, the simulator is fully capable of reproducing the behavior of the tested PHEVs, at any temperature between −2°C and + 35 °C, for a various range of driving profiles and trip lengths, and under any state of charge of the battery. The simulator also provides an extension to any battery capacity between 2 kWh and 35 kWh (knowing that the tested vehicles were equipped with a 13.5 kWh battery) and to a non-plug-in HEV (which is basically 120 kg lighter and working only in CS mode as it cannot be recharged). Although this is already a significant range of configurations which can be simulated, the results cannot be extrapolated to any other PHEV, having for example other engine or electric power or other energy management strategies (e.g. switching the engine on to heat the cabin instead of using the battery).

3. Projection over comprehensive range of cases

In this part, a set of simulation results is generated, ideally over all possible vehicle conditions of use, aiming at extending the simulation results over a broad range of usage (and not only a specific RDE cycle). The above calibrated simulator is thus used as projections for a wide range of driving conditions and styles, weather temperatures, battery sizing and conditioning, etc.

Then, to easily forecast real-world sequences of PHEV usage, a simplified linear model was developed from the aforementioned database. Eventually, a light mathematical method is obtained, and can be used for predictions without having to run long simulations.

3.1. Simulations over a Design of Experiments (DoE)

3.1.1. Clustered cycles projection base

As projection base, IFPEN's clustered cycles was used (Pirayre et al., 2022). These cycles originate from GPS tracks recorded and downloaded from *Geco air* database. To build them, trip samples underwent unsupervised classifications based on statistical features, such as average/max speed, stop time, acceleration sparsity, etc. and road qualifications, mainly based on speed limit. Then for each cluster, speed profile was generated using Markov chain process.

Eventually, this provides for the 4 types of road in France (<30 km/h, < 50 km/h, < 90 km/h, < 130 km/h) a set of representative velocity profiles of characterized behavior. Indicated as "road Conditions", and marked ascending from 1 to 7, they stand for jammed circulation, moderate driving, growingly dynamic patterns, even harsh ones, and finally speeding (Table 2).

For comparison purpose, we added up the Artemis cycles typical for each of the 4 road types and WLTP homologation cycle. They are plotted in Fig. 6 among IFPEN's clusters against average speeds and 95th percentile of positive propulsion power. The latter stands as a statistically relevant upper limit in power demands distribution encountered along the driving cycle.

3.1.2. PHEV depletion modes

This paragraph describes the protocol with which CD and CS modes are simulated for each clustered cycle.

Components' heating behaviors were implemented and induce transient auxiliaries consumptions. Therefore, it is not possible to

Table 2
DoE cycles categorization including IFPEN's cluster-based generated cycles.

Inner City	Outer City	Extra Urban	Highway
roadType1-roadConditions1	roadType2-roadConditions1	roadType3-roadConditions1	roadType4-roadConditions1
		roadType3-roadConditions2	roadType4-roadConditions2
		roadType3-roadConditions3	roadType4-roadConditions3
roadType1-roadConditions5	roadType2-roadConditions5	roadType3-roadConditions4	roadType4-roadConditions4
	roadType2-roadConditions6	roadType3-roadConditions6	roadType4-roadConditions5
roadType1-roadConditions7	roadType2-roadConditions7	roadType3-roadConditions7	roadType4-roadConditions7
Artemis TJam	**Artemis Urb**	**Artemis Road**	**Artemis Mot**

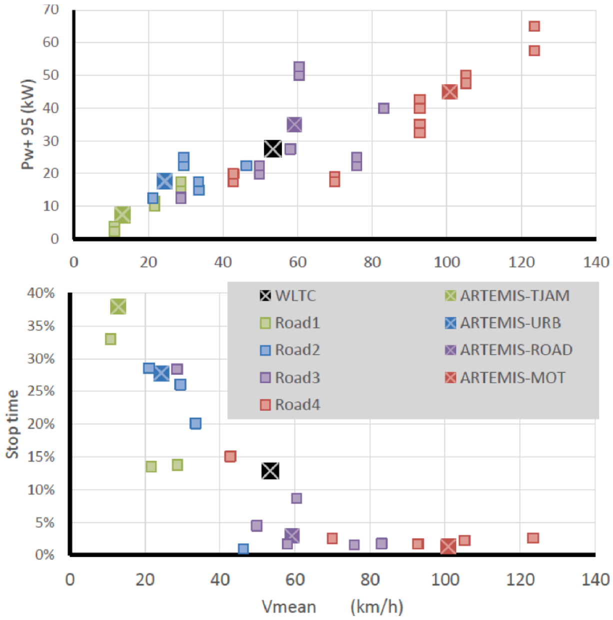

Fig. 6. Clustered cycles positioning compared to common benchmarks in the view of some of the most consistent features ("Pw + 95" means 95th percentile of positive propulsion power).

settle solely for one vehicle CD and one CS achieved under standard conditions to recombine all possible results. Therefore, the following was performed:

- a complete succession of depleting cycles until PHEV has reached SoC targeted threshold,

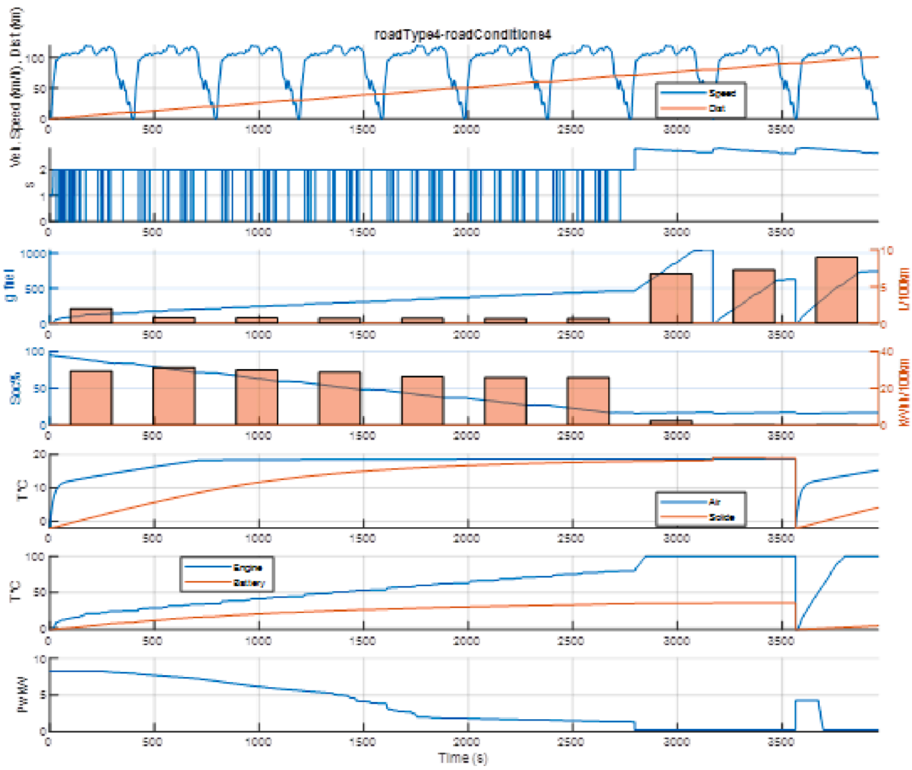

Fig. 7. Concatenated simulation results for repeated sequence of moderate driving highway cycle.

- then, a “hot CS” relevant for vehicle asymptotic consumptions once every component has been heated up,
- finally, a “cold CS” starting with all components at outside temperature, as if battery had not been charged (~HEV vehicle).

All the possible shades of sustaining modes reached with some heating left to achieve (because depleting phase was not enough to reach vehicle’s thermal steady state) are supposed to lay between these last two extreme CSs. For instance, a small or partially charged battery might empty before cabin and battery are totally conditioned: vehicle will then switch to charge sustaining with starting conditions somewhere between “Cold CS” and “Hot CS”.

The example illustrated in Fig. 7 of highway moderate driving shows that PHEV switches from depleting to sustaining mode at the very beginning of the 8th cycle repetition. As a consequence, 8th cycle fuel consumption becomes very close to “Hot CS” simulated right after it. Such depleting sequence puts forward the effect of transient thermal behavior and of engine coming up to temperature allowing to switch off cabin heater. It thus shows progressive drop in auxiliaries power that result in CD electrical consumption to fall from ~ 30 kWh/100 km to ~ 25 kWh/100 km towards the end battery use. With the same pattern, charge sustaining fuel consumption is significantly higher over the last cycle than during its predecessor, because of heater requirement and cold engine overconsumption under low initial temperatures operation.

Transition cycle results are deliberately obviated since it would be complicated to sort out which consumptions share to attribute respectively to CD and CS.

3.1.3. Vehicles configurations

Each depleting and sustaining sequence described above for each clustered cycle is simulated for cold (-2°C), temperate (+23 °C), and warm (+35 °C) outside/initial temperature. Moreover, all situations are performed with both the gasoline and Diesel versions of the PHEV.

Finally, our simulation matrix is multiplied by the 3 different battery capacity options:

- 13.5 kWh, actual Mercedes C300e/de battery capacity, allowing around 50 km of All Electrical Range (AER) under homologation cycle (WLTC) and conditions,
- 25 kWh, next generation benchmark, already starting production, aiming to reach 100 km AER in standard conditions,
- 7 kWh, previous generation observed capacity.

The battery calibrated thermal capacity is supposed to change proportionally to its actual capacity, compared to the reference set up at 13.5 kWh. Virtually, the bigger the battery, the greater the amount of electricity needed to bring it to optimal temperature. Since the study addresses the question of optimal battery capacity (among others), it is supposed that energy density is independent of battery capacity, hence the proportionality between thermal and storage capacities.

3.1.4. DoE overview

The simulation matrix has five dimensions, summarized in Table 3: ICE type (2 levels), PHEV mode (3 levels), driving cycle (24 levels), battery capacity (3 levels) and outside temperature (3 levels). It results in 1296 possible combinations, which were all simulated. But in fact, >3000 simulations were performed and provided detailed results, because of the variable number of successive depleting cycles necessary to drain battery.

3.2. Analytical model rendering

Although simulation can provide any result from any situation once it is properly calibrated, it remains a time-consuming process that cannot be generalized to each practical application. As the study intends to aggregate day-to-day PHEV users’ patterns over a whole population, it is needed to design a simpler analytical method by using the previously generated database. Instead of rerunning simulations, a mathematical post-processing method was developed, bringing the results altogether.

3.2.1. Results linearization principle

The previous paragraphs showed that simulated energy consumptions seem to converge towards asymptotic levels after transient warm-up. Therefore, the concept behind the mathematical process developed in this study consists in identifying the asymptotic

Table 3
Simulation DoE dimensions and features.

Dimensions explored	Number of variations	Values
ICE type	2 combustion modes	Gasoline, Diesel
PHEV mode	≥3 initial SoC	CD 95 % until 15 % depletion + CS hot + CS cold
Driving cycle	5 + 19 speed profiles	WLTC, ARTEMIS x4 [Road Type 1->4] x [Road Conditions (1)->7]
Battery capacity	3 capacities	7 kWh, 13.5 kWh, 25 kWh
Outside Temperature	3 initial T°	−2°C, 23 °C, 35 °C

(lowest) values of energy consumption for each speed profile, to which overconsumptions (i.e. deviations) are then added. Since the latter correlate with thermal conditioning, it is needed to quantify progression unified scales relevant to vehicle's components. For that purpose, the following deviation variables are defined:

$$\begin{cases} \Delta\mathrm{Tbat_i} = Max(0,\ 35^{\circ}\mathrm{C} - \mathrm{Tbat_i}) \\ \Delta\mathrm{Tcab_i} = Max(0,\ 19^{\circ}\mathrm{C} - \mathrm{Tcab_i},\ \mathrm{Tcab_i} - 23^{\circ}\mathrm{C}) \\ \Delta\mathrm{Teng_i} = 100^{\circ}C - \mathrm{Teng_i} \end{cases} \tag{1}$$

$$\Delta\mathrm{Tenv} = \mathrm{abs}(\Delta\mathrm{Tenv} - 23^{\circ}\mathrm{C}) \tag{2}$$

The equations (1) and (2) bring forward the gap between actual and final (i.e. asymptotic) temperatures for the battery (optimal range 35 °C ~ 40 °C), the cabin (passenger comfort 19 °C ~ 23 °C), and engine (hot operation 100 °C). The last formula states how far from standard temperature (23 °C) the vehicle's environment is. This allows to quantify steady state contribution: it corresponds to a permanent term to which transient consumption to reach target temperatures is added.

To keep the mathematical model as simple as possible, simple functions (linear if possible) were investigated, and the best response was obtained with surfaces fittings (least squares method) with the 2D combinations illustrated in Fig. 8 showing RoadType4-RoadConditions5 example.

Starting with battery's electricity consumption in upper left graph, minimum energy rate in CD (dotted, squares are for CS and are considered as zero) appears in green at the surface closest corner:

- Any displacement along X-axis induces overconsumption because battery and cabin still need to be heated up or cooled down. As they both have approximately the same dynamic, their respective deviation effects can be tangled.
- Any displacement along Y-axis means steady state overconsumption due to power required to maintain cabin temperature in warm or cold outside conditions.

Regarding electricity consumption, any combination of the 2 dissociated dimensions can be modelled using simple linear coefficients, as shown in equations (3) and (4):

$$\begin{cases} \mathrm{Cons_i^{Batt}} = \mathrm{Cons0_i^{Batt}} + \alpha_i \Delta\mathrm{Tbat_i} + (\alpha_i\ \Delta\mathrm{Tcab_i} + \beta_i\ \Delta\mathrm{Tenv}).\mathrm{Heat_{OFF}}\, underCD \\ \mathrm{Cons_i^{Batt}} = 0 underCS \end{cases} \tag{3}$$

$$\mathrm{Heat_{OFF}} = (\Delta\mathrm{Teng_i} > 50^{\circ}\mathrm{C} \cup \mathrm{Tenv} > 23^{\circ}\mathrm{C}) \tag{4}$$

To get clean surfaces, some data points at −2°C had to be graphically relocated because of the cabin heater being turned off. Indeed, thanks to engine reaching 50 °C at least, the cabin is provided with free heat from the engine coolant, and such −2°C points can virtually be considered as standard 23 °C, hence the deviations terms cancel out in formulas. For the sake of simplification and because it appeared to be of 2nd order influence, SoC levels are not discriminated and points relative to different battery capacities are mixed up. This might explain some of small discrepancies visible on response surfaces.

For fuel consumption (upper right graph in Fig. 8), the same 2D linear learning method can be implemented. In the equation (5), the affine formulation of the fuel consumption on CS is similar to the one just described for the electrical energy, including the rebasing of the points related to the heating shutdown. CD fuel consumption is simplified solely to X-axis dependency, with a 70 °C offset on engine temperature. The deviation of the engine temperature from its set point is the descriptor that replaces that on the battery temperature.

$$\begin{cases} \mathrm{Cons_i^{Fuel}} = \mathrm{Cons0_i^{CD}} + \mathrm{C_i}\,(\mathrm{Max}(0,\ \Delta\mathrm{Teng_i} - 70^{\circ}\mathrm{C}) + \Delta\mathrm{Tcab_i}.\,\mathrm{Heat_{OFF}}) \quad \text{under CD} \\ \mathrm{Cons_i^{Fuel}} = \mathrm{Cons0_i^{CS}} + \mathrm{A_i}\,\Delta\mathrm{Teng_i} + (\mathrm{A_i}\,\Delta\mathrm{Tcab_i} + \mathrm{B_i}\,\Delta\mathrm{Tenv}).\,\mathrm{Heat_{OFF}} \quad \text{under CS} \end{cases} \tag{5}$$

Thankfully, linearization patterns also work to model Utility Factors, still with outside temperature deviation for steady state and

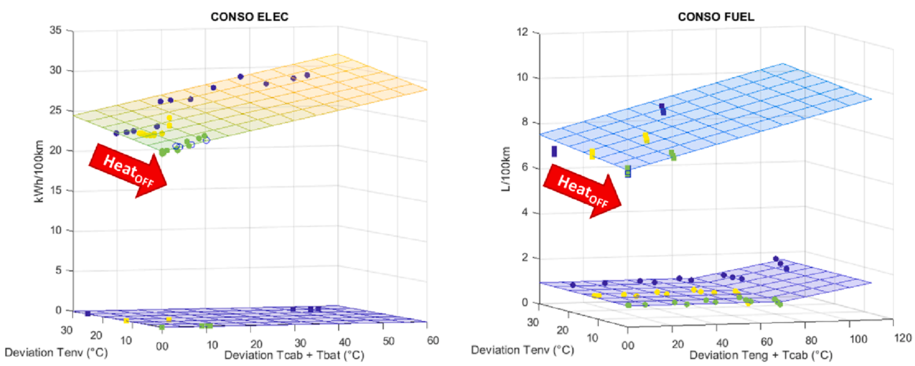

Fig. 8. Fast highway driving example of linear learning method (each dot and square represents an actual simulation result).

deviations term disabling for hot engine, as shown in Fig. 9. However, engine/cabin/battery cumulated deviations are here considered for X-axis transient effect. Under CD mode, both upper response surfaces (dots) show 100 % electric drive or close. On the contrary, CS mode surfaces (squares) implies degradation of electric share much more responsive to temperature deviations for Road1 profile (left) than for Road4 (right).

3.2.2. Temperature deviation assessment

We now have established that electrical and fuel consumptions can quite confidently be calculated with linear combinations of vehicle temperature deviations. Yet, these thermal progression indicators still need to be assessed. For that purpose, temperatures evolution rates over driven kilometers were estimated during database post-processing.

Concerning cabin and battery temperature deviations, their derivatives (to distance) appear quite remarkably proportional to their own value (Fig. 10), which is consistent with proportional command implemented in the simulator. This means that a first order solution using slope coefficient interpolated from considered driving cycle can easily be implemented over driven kilometers in transient exponential profile below (equations (6) and (7)). For simplification's sake, battery temperature derivative is specified in comparison to its capacity.

$$\Delta \mathrm{Tbat}_i(\mathrm{Km}) = \Delta \mathrm{Tbat}_i^0 \, e^{-\lambda_{bat}^i \cdot \mathrm{Km}} \tag{6}$$

$$\Delta \mathrm{Tcab}_i(\mathrm{Km}) = \Delta \mathrm{Tcab}_i^0 \, e^{-\frac{\lambda_{cab}^i}{C_{Batt}} \cdot \mathrm{Km}} \tag{7}$$

Engine temperature derivative over distance is a bit more elaborated. Its 3D shape stays logically close to the corresponding fuel consumption response surfaces, since engine warm-up was calibrated in the simulator proportionally to the amount of burnt fuel. A first order solution still exists for engine temperature progression profile.

3.2.3. Mathematical implementation

Thanks to an adapted regression routine, energy consumption rates restitution has been mathematically narrowed to a linear combination of constants and exponential functions showing components transient behavior (equation (8)). This results into analytical solutions for cumulative scores, easily integrated over driven kilometers, as formalized with the next practical example.

$$\mathrm{kWh}_i(\mathrm{Km}) = \mathrm{Cons0}_i^{\mathrm{kWh}} \, \mathrm{Km} + \beta_i \, \Delta \mathrm{Tenv} \, \mathrm{Km}^{**} + \alpha_i \, \Delta \mathrm{Tbat}_i^0 \, \frac{1 - e^{-\lambda_{bat}^i \, \mathrm{Km}}}{\lambda_{bat}^i} + \alpha_i \, \Delta \mathrm{Tcab}_i^0 \, \frac{1 - e^{-\lambda_{cab}^i \, \mathrm{Km}^{**}}}{\lambda_{cab}^i} \tag{8}$$

For each driving cycle *i*, each contribution - constant temperature regulation, warm-up – can be identified. The corrected integration distance Km** (equation (9)) should be carefully considered, above which heater is turned off thanks to engine coolant temperature exceeding 50 °C and thus integrating overconsumption can be stopped.

$$\mathrm{Km}^{**} = \begin{cases} min\left[\mathrm{Km}, \dfrac{\mathrm{Max}\left(0, \, \Delta \mathrm{Teng}_i^0 - 50^\circ \mathrm{C}\right)}{K_{eng}^i}\right] ifTenv \leq 23^\circ C \\ KmifTenv > 23^\circ C \end{cases} \tag{9}$$

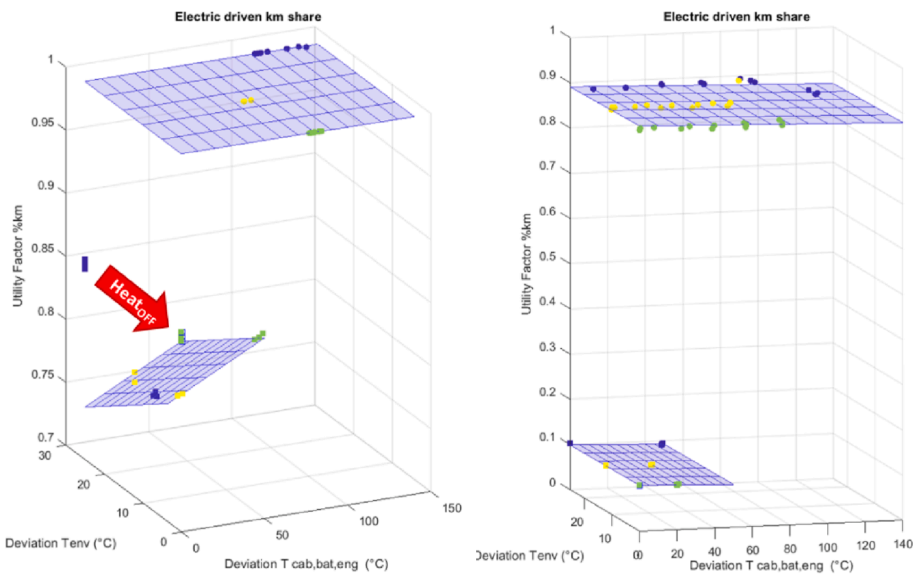

Fig. 9. Fast driving highway cycle example of linear response surfaces to predict UFs: Road1 profile (left), Road4 profile (right).

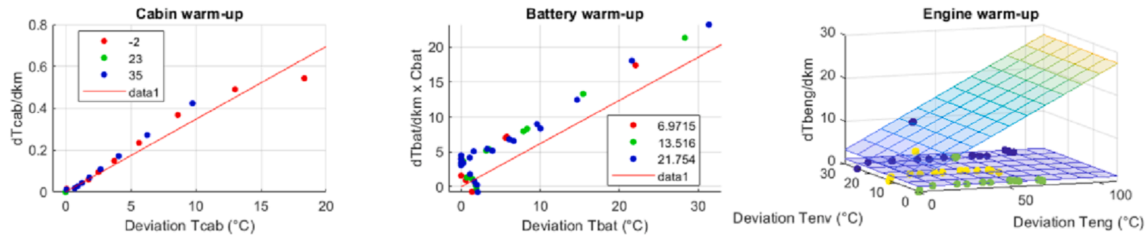

Fig. 10. Fast driving highway cycle example of temperature deviations results linearization - Graph 1 (cabin temperature): each dot represents a simulation result by class of ambient temperature - Graph 2 (battery temperature): each dot represents a simulation result by class of battery capacity – Graph 3 (engine temperature): each dot represents a simulation result by class of ambient temperature.

Once consumptions over any clustered cycle can be calculated, they can be summed into the process pictured by the flow chart below (Fig. 11) to obtain real-world vehicle solicitation. The latter, which is divided into a sequence of identified speed profiles, is provided as cycles list and respective mileages, along with vehicle's characteristics and weather conditions. Thereby in a loop pattern, temperatures deviation profile and then consumptions are successively estimated for each segment. Eventually, the addition of all segments indicates the total amounts of electricity and fuel required in this specific use.

Fig. 12 illustrates such a practical example through a countryside to inner city trip. For that, one considered the C300e equipped with a full 25 kWh battery driven by a cold −2°C day 10 km on road, then 60 km on highway, entering 10 km of city, and finishing with 3 km of city center.

Obviously, one cannot expect to get time resolved detailed curves from our analytical approach: the vehicle physical behavior is considered homogeneous along each distinctive segment characterized in top chart indicators (speeds & power 95th percentile). Yet, the 1st order transient warm up can be observed on the 3rd chart showing engine/cabin/battery temperature deviations progression. Its direct impact on consumptions can also be observed in the 2nd chart, as they progressively drop to their asymptotic values.

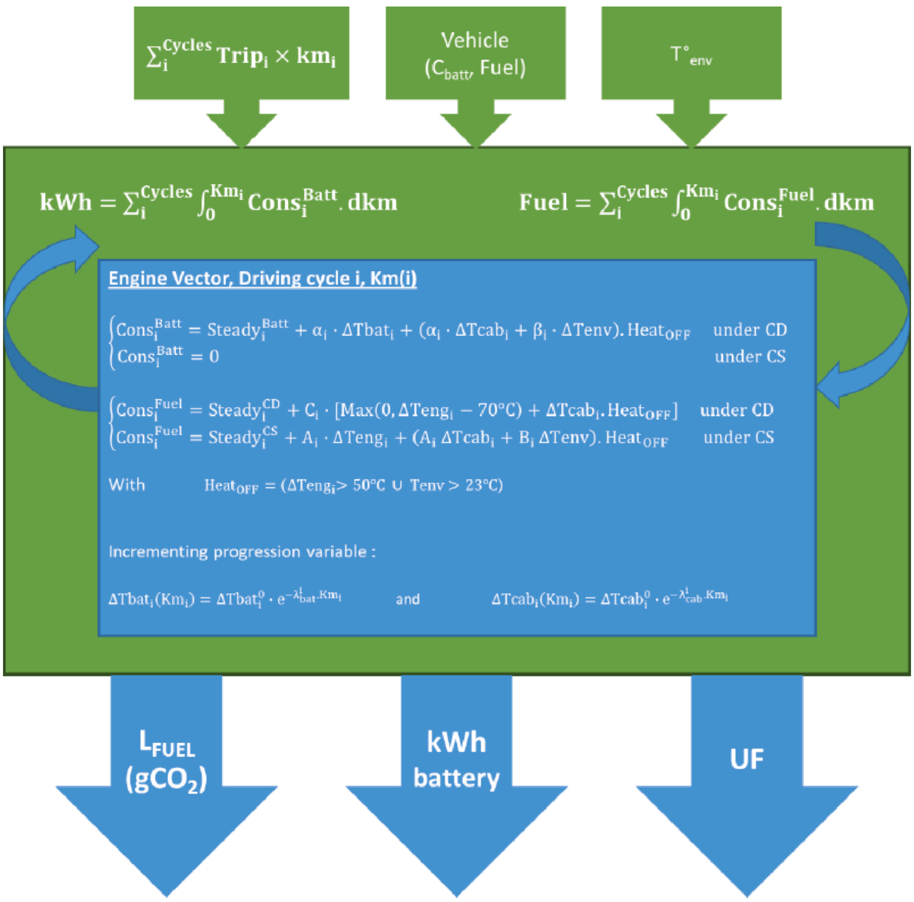

Fig. 11. General processing sketch of PHEV behavior analytical assessment.

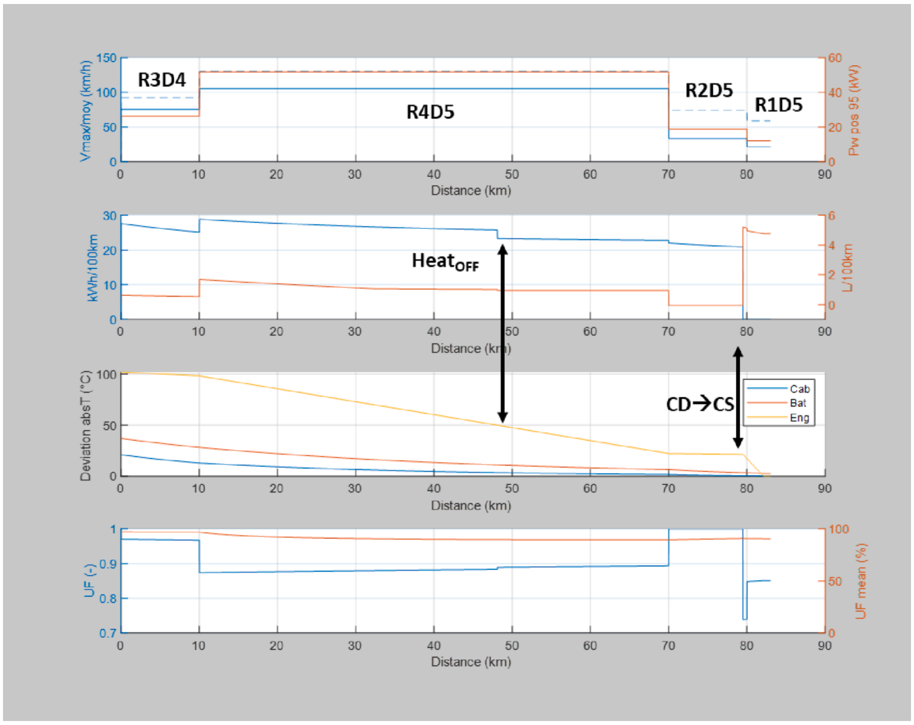

Fig. 12. Time-resolved example of analytical model practical exercise other country to city sequence.

Aside from switches from a driving pattern to the next one that induce expected steps, singularities are recorded when:

- engine coolant temperature reaches 50 °C, inducing a sudden drop in consumptions thanks to coolant heat availability,
- electrical and fuel consumptions overturn because of CD to CS transition.

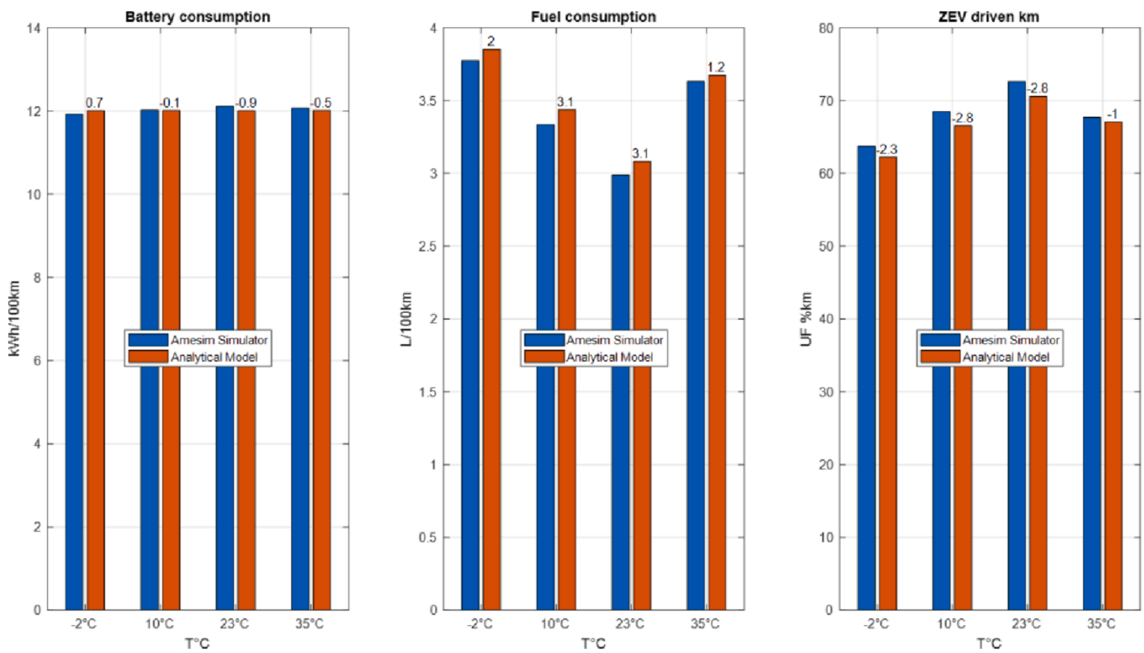

Fig. 13. Simulation vs mathematically assessed driving sequence for the complete range of ambient temperatures. Values on top of the bars are the % difference between the results of the two simulation methods.

3.2.4. Mathematical model validation

In accordance with the previous example, the same sequence is parametrized as a whole and re-run as a single cycle in the vehicle physical simulator. Both simulation results are then compared in Fig. 13: only a few percent gaps between the two methods are observed, which validates the analytical model. Moreover, an intermediate case at 10 °C was tested for further successful verification. Finally, it can be concluded that the mathematical model is predictive in the range of modelled ambient temperatures [−2 °C, 35 °C].

4. Results over generalized usage

Due to the degrees of freedom induced by the architecture of PHEVs, they are extremely versatile: equally capable of operating almost exclusively on electrical or chemical energy depending on the conditions of use. It is therefore necessary to assess the actual behavior of PHEVs:

- by evaluating the sensitivity of technologies to the conditions of use,
- by assigning a weighting to each condition according to its representativeness.

For instance, the WLTP certification procedure, which includes a full battery test, an empty battery test, and a weighting between those two resulting from a strong hypothesis of daily charging and daily distance distribution, also applies these two necessary steps.

Thanks to the simulation work, it is proposed to go further by:

- considering more sensitivities of technologies (particularly to ambient temperature),
- considering more usage statistics,
- not necessarily considering daily recharging but a whole range of recharging frequencies,
- varying the size of the battery.

4.1. Capturing the sensitivity of technologies: Assessment of results on a large matrix

Based on the analytical model described above, each individual use case is simulated as a combination of:

- v conditions of daily vehicle kilometers travelled (VKT) and associated driving patterns, 24 cases [4:400 km]
- **t** conditions of ambient temperature, 20 cases [-2:36 °C]
- **r** conditions of recharge interval, 11 cases [0.5:10 days]

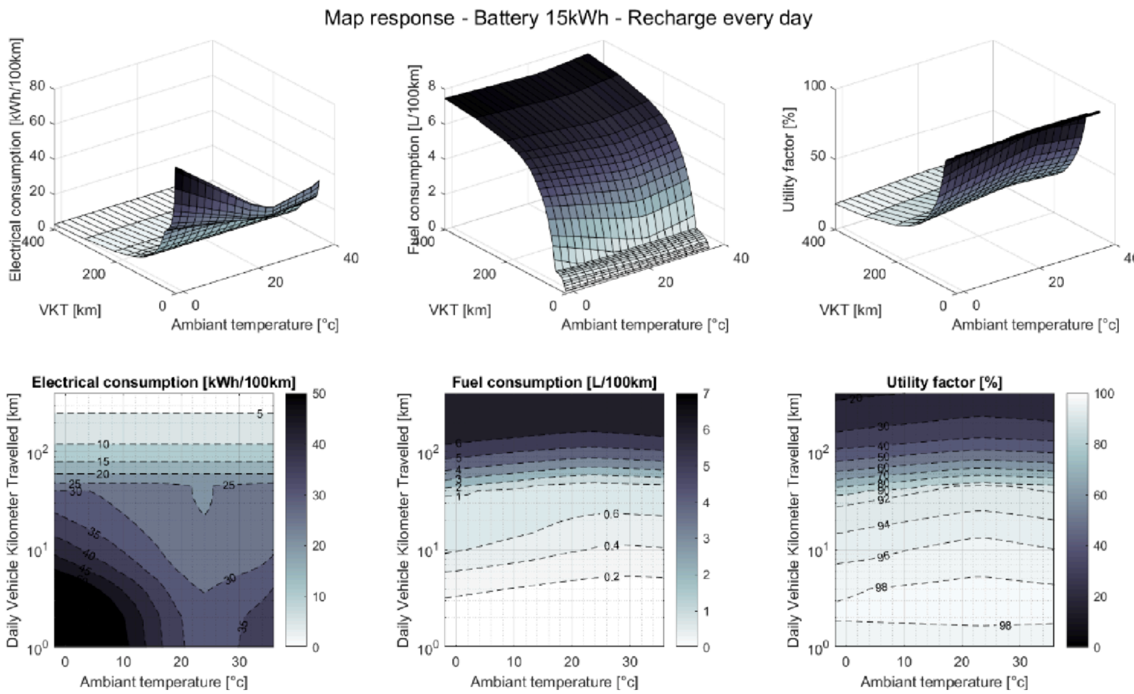

Fig. 14. Example of results, for one given battery capacity and recharge frequency (Gasoline PHEV with a 15 kWh battery recharged every driving day).

- **b** conditions of battery sizing, 10 cases [2:35kWh]

Fig. 14 shows the results of simulations made for one given value of battery capacity (15 kWh) and recharge frequency (every day) for the gasoline PHEV. A total of 480 combinations of temperature/daily mileage are considered.

The simplified mathematical model reproduces the behavior of the physical model, and therefore also of the vehicles evaluated experimentally. It can be observed a plateau of high Utility Factor values (>95 %) for short distance trips (<20 km) as a PHEV recharged every day is able to handle these distance almost completely in all-electric mode. In this area, a low fuel consumption is consistently observed and a high electrical consumption is stated. A sharp increase in power consumption in cold ambient conditions is observed as a consequence of battery and cabin conditioning. As trips become longer, the battery SoC decreases, resulting in a sharp decrease of the Utility Factor. Consequently, the average electrical consumption decreases and the average fuel consumption increases sharply with trip distance, and even more at low temperature due to the decrease of the electric range caused by the battery and cabin heating.

The same simulations were performed for every battery size [2 to 35kWh] and recharge interval [0.5 to 10 days], for both Diesel and gasoline vehicles, leading to around 53,000 use cases simulated including variation of technology sizing, environmental and driving conditions.

4.2. *Statistics of use: Representativeness of each use case*

As seen above, the most influential parameter on the behavior of a PHEV for a given charging interval is the daily distance travelled. Furthermore, as is the case for highly electrified vehicles in general, the electrical consumption of PHEVs is particularly sensitive to ambient temperature conditions.

This paragraph focuses on the statistical distributions of use observed for these two influencing parameters, extracted from the literature and from an internal database. These statistical distributions will then be used to weight the different use cases according to their probability.

4.2.1. *Ambient temperature*

Through the *Geco air* application, IFPEN has collected daily mobility data from thousands of non-professional drivers. Although the application is available across Europe, most users are located in France. The frequency of temperature recorded during each trip (weighted by distance) is shown in Fig. 15. The average temperature of 12.8 °C is slightly below the average annual temperature in mainland France (around 13.8 °C).

This distribution is approximated by a gamma distribution law (equations (10) and (11)), as illustrated in Fig. 16:

$$P(t; k, \theta) = \frac{(t - t_0)^{k-1} e^{-\frac{t-t_0}{\theta}}}{\Gamma(k)\theta^k} \tag{10}$$

$$k = 15.74\,;\ \theta = 2.017\,;\ t_0 = -18.99 \tag{11}$$

To study the climatic sensitivity, this same distribution is shifted by an offset of + 10 °C and −10°c to arbitrarily represent warmer and colder climate conditions. The average temperatures thus reproduced are respectively close to the average Australian (22 °C) and Swedish (2 °C) temperatures.

4.2.2. *Daily vehicle mileage travelled*

The utility factors defined by the WLTP protocol for the type-approval of PHEVs come from mobility studies determining the daily distances operated. Assuming daily charging, they represent the possible electrification percentage of the distance covered by a fleet according to the vehicle's electric range.

Other data are available in the literature, in particular from mobility surveys in Germany (Plötz et al., 2012) and across Europe (Paffumi et al. 2018). These data are used for the rest of the study thanks to the availability of the coefficients of the laws which fit the data sets. Data from the JEMA database are approximated by a polynomial distribution in Paffumi et al., while data from the German mobility survey are in Plotz et al. approximated by a log-normal law. They are shown in Fig. 17.

Fig. 18 represents more specifically the log-normal distribution (equation (12) and (13)) from the German mobility survey by Plotz et al. for the "medium" vehicle class.

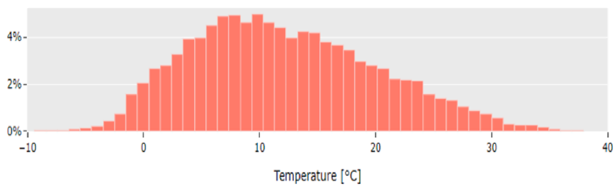

Fig. 15. Distribution of the ambient temperature while driving (weighted by travelled distance) – IFPEN data (*Geco air*).

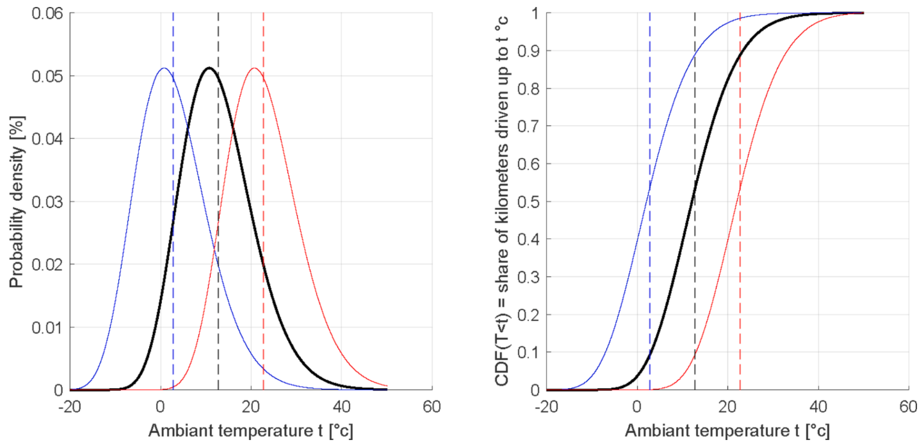

Fig. 16. Ambient temperature distributions retained for the current work. Black curves: central case (France); blue curves: colder case; red curves: warmer case. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

$$Prob(d;\mu,\sigma) = \frac{1}{d\sigma\sqrt{2\pi}}\exp\left(-\frac{\ln(d)-\mu}{2\sigma^2}\right) \tag{12}$$

$$\sigma = 0.81\,;\,\mu = 3.3\,; \tag{13}$$

It is important to clarify that these probabilities are distance-weighted and not vehicle-weighted: the cumulative distribution function CDF(X) represents the share of the total distance travelled by the fleet that is operated with vehicles traveling less than X kilometers per day. This is different from the share of vehicles traveling less than X kilometers per day.

Other studies are available (Xing et al., 2020; Plötz et al., 2017; Wang et al., 2013; Boston and Werthman, 2016) but without access to the raw data or to the coefficient of the distribution laws obtained, which does not make them relevant in the context of this study.

4.2.3. Driving pattern (function of VKT)

The type of route also has an impact on energies (electricity and fuel) consumption levels and Utility Factor. In the IFPEN database, as illustrated in Fig. 19, the share of kilometers travelled in slow urban, urban, rural and motorway conditions is determined as a function of VKT. The equations (14), (15), (16) and (17) are then fitted to this data. For the sake of simplification, the adopted order of the driving order was always from the slowest (slow urban) to the fastest (motorway).

$$r_{slow}(vkt) = \left(\frac{vkt}{a_{slow}}\right)^{-b_{slow}} + c_{slow} \tag{14}$$

$$r_{urban}(vkt) = \left(\frac{vkt}{a_{urban}}\right)^{-b_{urban}} + c_{urban} \tag{15}$$

$$r_{mty}(vkt) = a_{mty} + b_{mty}\log(vkt + c_{mty}) \tag{16}$$

$$r_{rural}(vkt) = 100 - r_{slow}(vkt) - r_{urban}(vkt) - r_{mty}(vkt) \tag{17}$$

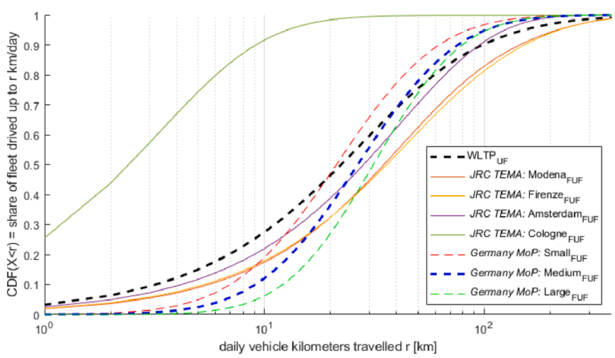

Fig. 17. Cumulative frequency distribution of daily vehicle kilometers travelled, issued from literature.

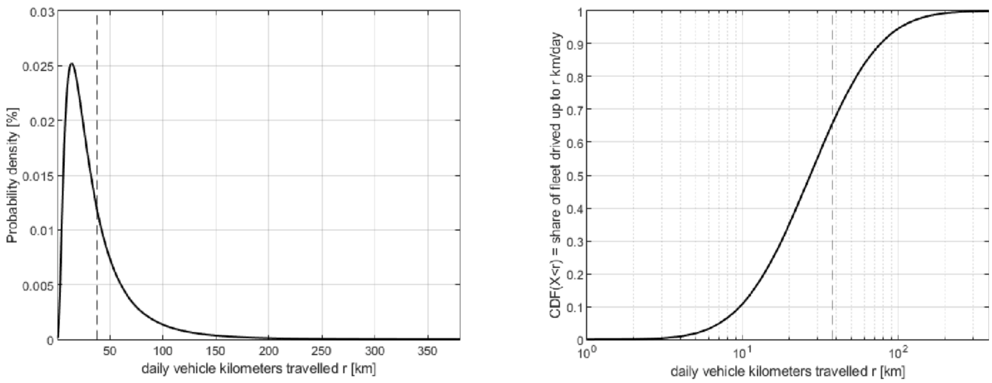

Fig. 18. VKT distribution retained for the current work.

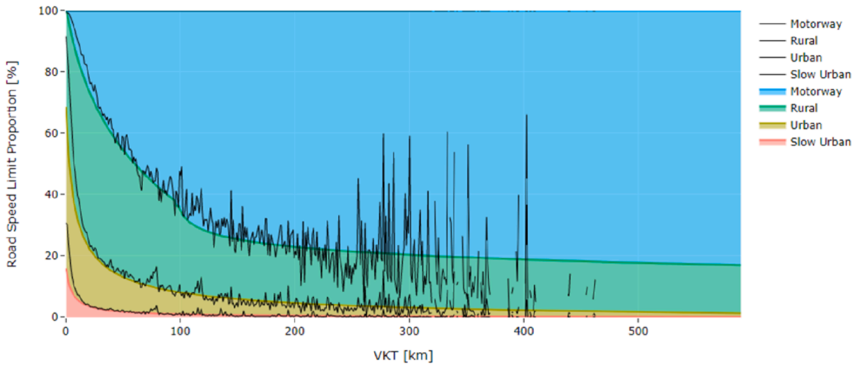

Fig. 19. Typology of road function of daily mileage.

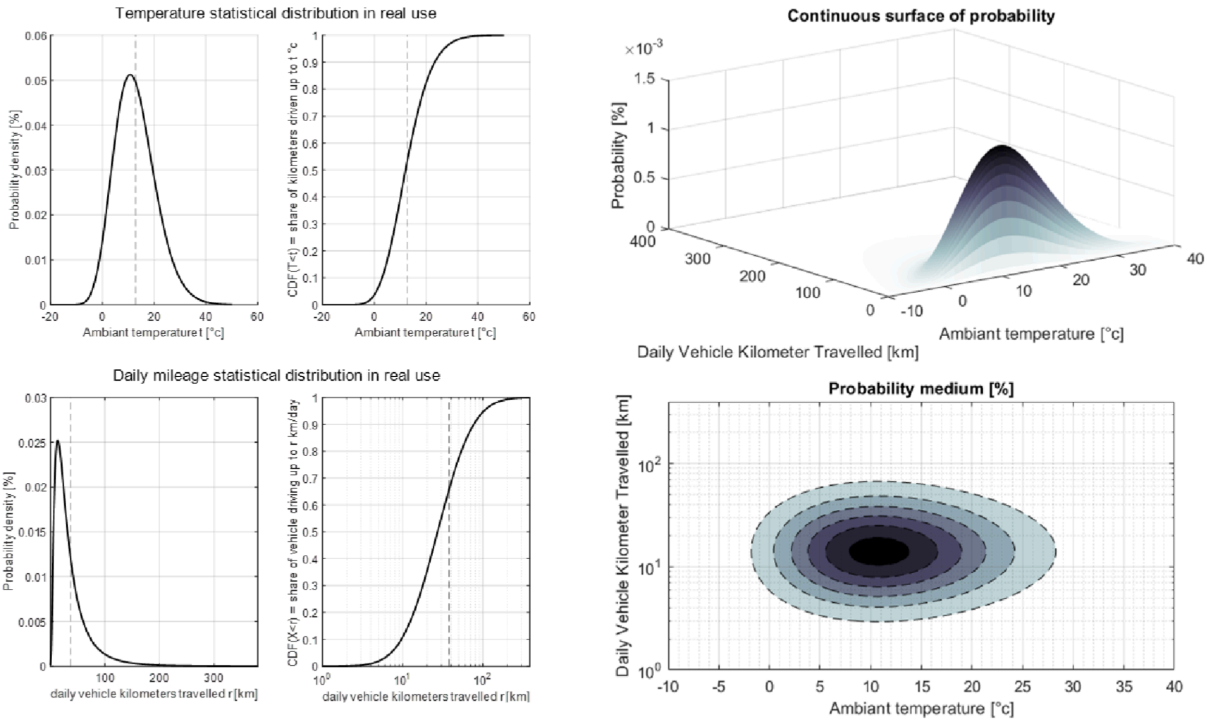

Fig. 20. Matrix of use cases probability function of ambient temperature and daily mileage.

4.2.4. Resulting probability matrix

Assuming that temperature and trip distance are independent (the distribution of VKT remains the same whatever the ambient temperature), the probability of a couple VKT-ambient temperature is obtained by the multiplication of the laws previously established for the VKT and the ambient temperature. Thereby, considering the driving temperature distribution in France and the daily vehicle mileage issued form literature (Germany mobility survey), a probability matrix is determined and makes it possible to determine the probability of each situation in real-world conditions (Fig. 20).

4.3. Weighted average outputs

For each couple of battery capacity and recharge frequency, weighted average values are calculated taking into account each individual use case on the whole range of VKT and ambient temperature and its representativity (equations (18), (19) and (20)):

$$EC_{r,b} = \sum_{v}\sum_{t} prob_{v,t} \times ec_{v,t,r,b} \tag{18}$$

$$FC_{r,b} = \sum_{v}\sum_{t} prob_{v,t} \times fc_{v,t,r,b} \tag{19}$$

$$UF_{r,b} = \sum_{v}\sum_{t} prob_{v,t} \times uf_{v,t,r,b} \tag{20}$$

Where,

- v: the daily vehicle kilometers travelled (VKT) and associated driving patterns, 24 cases [4:400 km];
- t: the ambient temperature, 20 cases [-2:36 °C];
- r: the recharge interval, 11 cases [0.5:10 days];
- b: the battery capacity, 10 cases [2:35kWh];
- $prob_{v,t}$: the probability of the use case (v,t);
- $ec_{v,t,r,b}$, $fc_{v,t,r,b}$ and $uf_{v,t,r,b}$ respectively the electrical consumption, the fuel consumption and the utility factor for a given VKT, temperature, recharge interval and battery capacity;
- $EC_{r,b}$, $FC_{r,b}$ and $UF_{r,b}$ respectively the weighted average electrical consumption, fuel consumption and utility factor for a given recharge interval and battery capacity.

Thus, for a given battery capacity and charging interval couple, mean scores representative of the actual use are obtained, resulting from the weighting of the energy performance in each use-case weighted by its representativeness (example in Fig. 21).

This was done for each pair of battery capacity-recharge interval, allowing to obtain the evolution of energy performance parameters in real-world conditions as a function of these two key parameters. Fig. 22 shows the weighted average outputs on the full range of variation for recharge interval and battery capacity. This figure is key to understand the sensitivity of real-world average energy performance (fuel and electrical consumptions and utility factor) of PHEVs to both the technological sizing and the final user behavior.

4.4. Sensitivity to ambient temperature and daily mileage distributions

The results presented above are based on the statistical distributions of ambient temperature and VKT presented in paragraph 4.2.4. It is proposed here to study the sensitivity of the model responses to these input parameters.

Fig. 23 shows a comparison between the weighted average results obtained for a gasoline PHEV equipped with 15 kWh battery

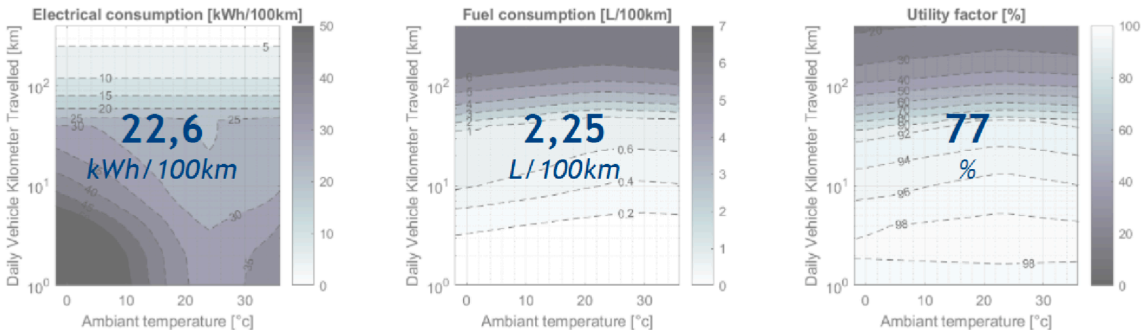

Fig. 21. Example of weighted average outputs for one given couple of recharge frequency and battery capacity (Gasoline PHEV with a 15 kWh battery recharged every driving day).

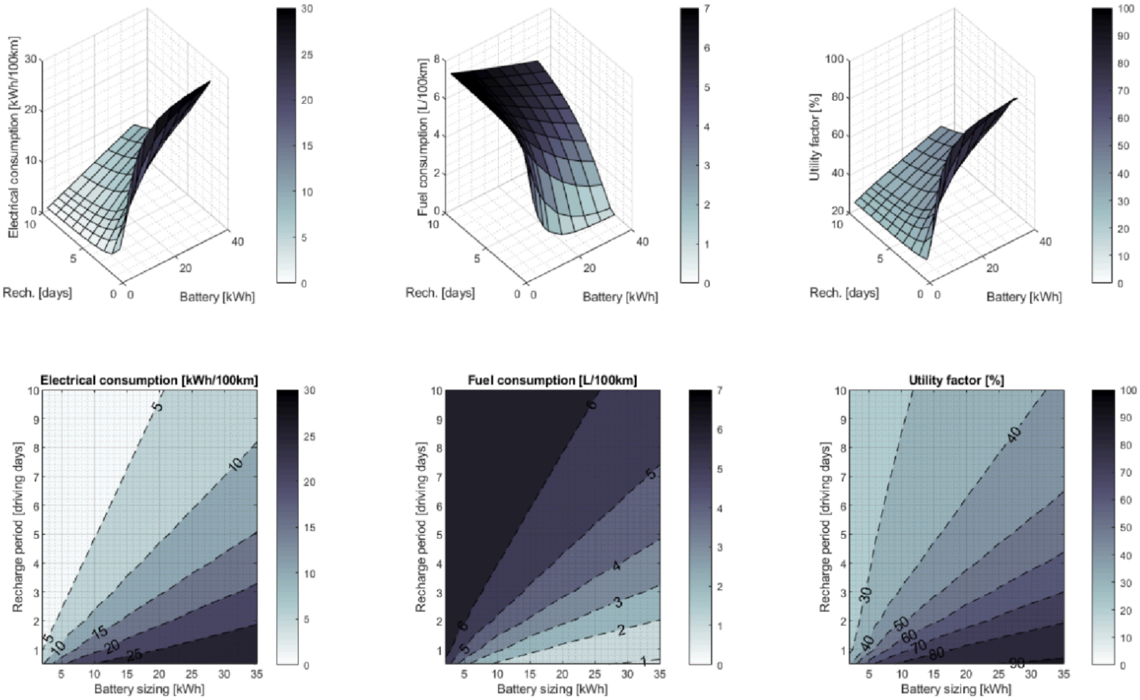

Fig. 22. Weighted average outputs on the full range of variation for recharge frequency and battery capacity.

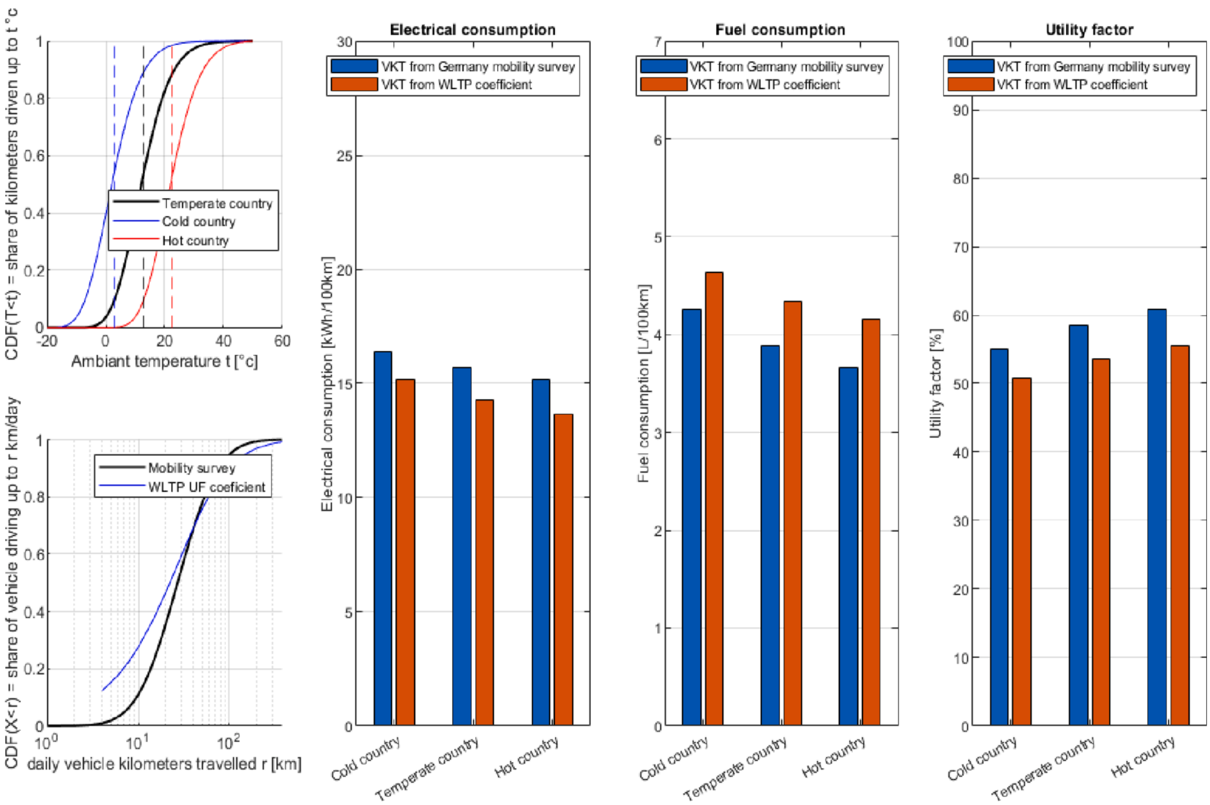

Fig. 23. Sensitivity to ambient temperature and daily mileage distributions – Gasoline PHEV equipped with a 15kWh battery and recharge frequency every 2 driving days.

recharged every-two driving days with different usage distributions:

- three ambient temperature distributions, called "temperate", "hot" and "cold", corresponding respectively to the distribution extracted from the IFPEN database in France, and two theoretical laws shifted by + 10 °C and −10 °C.
- two distributions of daily distance: the first one resulting from the German mobility survey for medium class vehicles, and the second one resulting from the WLTP protocol.

Whatever the VKT distribution law considered, the cold temperature case is the most critical one with increased electrical and fuel consumptions and reduced utility factor compared to the temperate and hot temperature cases. The hot law is itself less critical than the temperate law, which may appear counter-intuitive. This is due to the greater overconsumption induced by cold temperatures than by hot ones (see Fig. 14). Despite the higher induced air conditioning needs, the hot law is more centered on temperatures close to the living comfort temperature, and reduces the most penalizing heating needs.

Further sensitivities to statistical distributions of ambient temperature as a function of battery capacity and recharge frequency are shown in the Appendix E.

5. Discussion

5.1. Impact of battery capacity and recharge interval on PHEVs key results

Fig. 24 shows the weighted average fuel and electricity consumptions, CO_2 emissions and utility factor for the gasoline PHEV as a function of battery capacity and recharge interval, allowing to visualize the influence of the dimensioning of the battery according to the frequency of recharging.

Considering the technology sensitivity to real-world conditions (assessed during an experimental campaign, and reproduced in a simplified model), considering the statistical conditions of use around Europe (temperature and daily mileage), this approach allows to quantify the weighted average scores of PHEVs depending on their battery capacity and their recharge frequency:

- Quite intuitively, frequent recharging of PHEVs is a necessary condition for a high electrification rate: recharging every day allows to reach an average weighted fuel consumption of 2.25 L/100 km and utility factor around 77 % with a gasoline PHEV equipped with a 15 kWh battery. Recharging every 3 days instead induces a fuel consumption of 4.85 L/100 km (+116 %) and a UF around 48 % (-29 points).

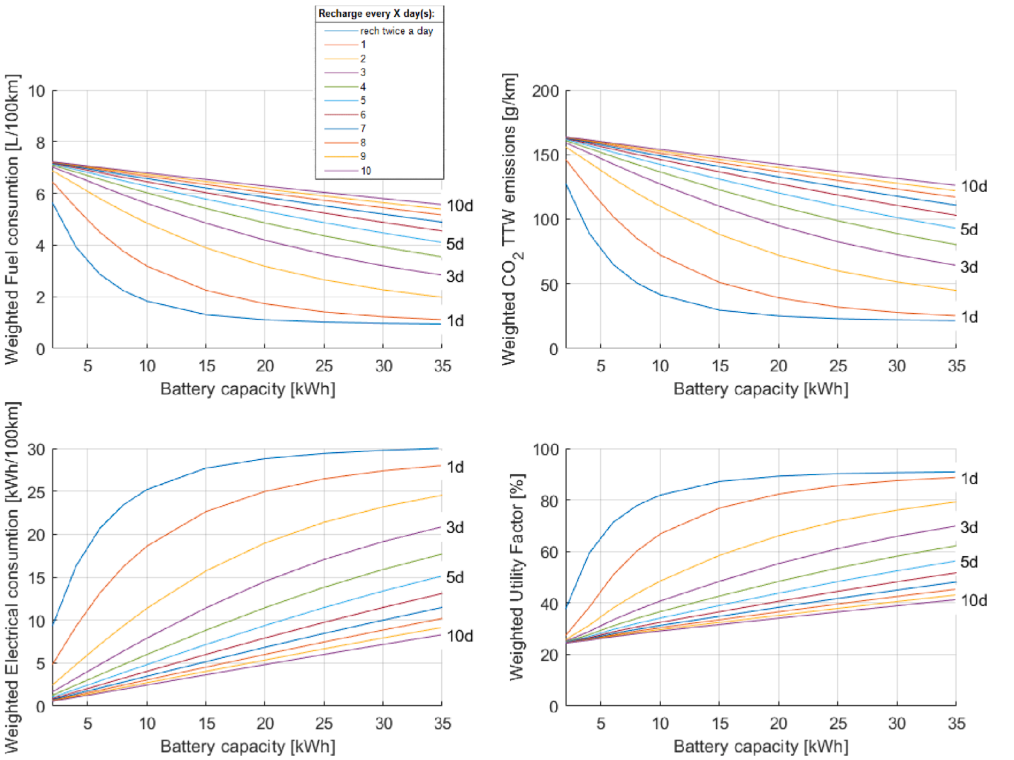

Fig. 24. Sensitivity of weighted average fuel consumption, CO_2 emissions, electrical consumption, and utility factor to the battery capacity (from 2 kWh to 35 kWh) and recharge frequency (from twice a day to every 10 days) – gasoline PHEV.

- A weighted average utility factor of 50 % is reached at around 6 kWh of battery capacity, and 80 % is reached at around 18 kWh of battery for an every-driving-day recharge.
- The first few kWh of battery are the most effective in reducing the weighted average fuel consumption: considering 1 recharge/day, the gain in increasing the battery above 20 kWh is low. For instance, adding another 15 kWh of battery to the vehicle, leading to a 30 kWh PHEV, would increase by only 10 points the utility factor, from 77 % to 87 %, if recharged every day; instead, the same 15 kWh battery could electrify 77 % of the mileage of another PHEV, which is more efficient if the total amount of available batteries is constrained (Shafiei et al., 2022).

As shown in Fig. 25, similar trends are observed for the Diesel PHEV results. A daily charge achieves a weighted average consumption of 1.94 L/100 km and a utility factor of around 77 % with a Diesel PHEV equipped with a 15 kWh battery. A charge only every 3 days induces a consumption of 4.10 L/100 km (+111 %) and a UF around 48 % (-29 points).

Fig. 26 provides a comparison between the two types of ICEs (gasoline vs Diesel). The larger the battery or the higher the recharging frequency, the more the difference between the fuel consumption and the UF of petrol and Diesel engines tends to narrow. Indeed, such conditions foster the use of more electric drive, and therefore minimize the impact of the performance of the internal combustion engines.

5.2. *Shifting from an individual vehicle evaluation to a systemic perspective*

To shift from the individual vehicle evaluation performed in this work to a systemic perspective, it is needed to link this work to the conclusions of (Shafiei et al., 2022).

In their study, (Shafiei et al., 2022) could not evaluate the UF of PHEVs by themselves and had to pick them from the literature based on data in (UNECE, 2017) and (ICCT, 2020), as shown in Table 4 and in Fig. 27. It is interesting to compare these UF with those obtained in this work, shown here in the case of the gasoline PHEV. It can be observed that the UF calculated for a recharge frequency every day is 4 to 8 points lower than the one given by the WLTP. It can also be seen that the UF calculated for a recharge every 5 days follows closely the one suggested by ICCT.

Based on the UF extracted in (UNECE, 2017) and (ICCT, 2020, Shafiei et al., 2022) calculated the optimal allocation of batteries to passenger cars to minimize their WTW GHG emissions, under various levels of battery supply to Europe, ranging between 0 and 1.2 TWh/year. Fig. 28 shows one of the major findings of their work: under constrained supply of batteries, it is better to allocate batteries to PHEVs first to minimize WTW GHG emissions; and only once the battery supply is less constrained, BEVs start to be part of the optimal solution, along with PHEVs first, and alone eventually. This conclusion reflects the fact that, 1- in the frame of a highly decarbonized electricity grid (assumed in 2030 in their work), electrifying the driven mileage leads to reduced WTW GHG emissions, and 2- to maximize the electrification of the driven mileage, it is more efficient to share smaller batteries used at their full capacity in all vehicles (allowed by PHEVs under constrained supply of batteries) rather than to allocate under-utilized bigger batteries to a few vehicles (result obtained if a BEV strategy is followed too early in the battery supply capacity). In addition, it is interesting to note that this conclusion is independent on any of the two UF used in their work, notwithstanding that the WTW GHG are lower when the UF is higher (because of more electrified mileage).

The question remains whether Europe will actually be under constraint of battery supply in 2030. Regarding the demand aspects, according to (Shafiei et al., 2022), supplying 0.95 TWh/year of batteries to passenger cars in Europe would allow to electrify them all, providing that their individual battery capacity is lower than 60 kWh; according to [Strat Anticipation, 2022], the demand for batteries in the EU for electrified light vehicles would be 0.894 TWh/year in 2030 (for BEVs equipped with a 78 kWh battery and sales which are not fully electrified), starting from 0.123 TWh/year in 2022, and through 0.365 TWh/year in 2025. Regarding the supply aspects, there have been significant differences in announced, revised and realistic output forecasts for battery production facilities ("Gigafactories") in the EU. For example, according to [Strat Anticipation, 2022], the EU planned output of batteries production for 2025 went down from 0.45 TWh/year (evaluated Q4 2021), through 0.392 TWh/year (evaluated February 2022) to 0.224 TWh/year, therefore requiring 0.141 TWh/year of imports; for 2030, the EU planned output was 0.80 TWh/year in Q4 2021, rose to 1.037 TWh/year in February 2022, and dropped to 0.609 TWh/year, therefore requiring 0.285 TWh/year of imports. It is unclear where the imports would come from, but they are unlikely to come from North America as its planned production output would also be lower than its demand, also resulting in an import balance; and forecasts in China's planned production output make China barely meet its internal demand.

In brief, it appears highly likely that the battery supply to passenger cars in Europe will be constrained for the next 10 years to come, and under these conditions (Shafiei et al., 2022) concluded that a vehicles sales mix oriented towards PHEVs would be optimal in minimizing the WTW GHG emissions.

Additionally, (Shafiei et al., 2022) looked further into the influence of the UF on the results of their optimizations. They found out that below a certain UF called "break-even utility factor", the PHEVs were no longer efficient in minimizing WTW GHG emissions, and therefore the structure of the passenger cars sales mix shifted directly from HEVs to BEVs without going through PHEVs (Fig. 29, left). Conversely, above the break-even utility factor, PHEVs play an important role in the transition between HEVs and BEVs to minimize WTW GHG emissions, and the structure of the passenger cars sales mix remains mostly unaffected whatever the utility factor above the break-even point (Fig. 29, center and right).

(Shafiei et al., 2022) generalized this approach and calculated the break-even utility factor for a variety of combinations of battery capacities for PHEVs and BEVs (shown as a function of their All Electric driving Range in Fig. 30). It can be seen that PHEVs with smaller batteries (e.g. PHEV 20) have a lower break-even utility factor: this is because smaller batteries can be shared with more vehicles which are more likely to use them at their full capacity, resulting in an efficient electrification of the overall mileage. For the

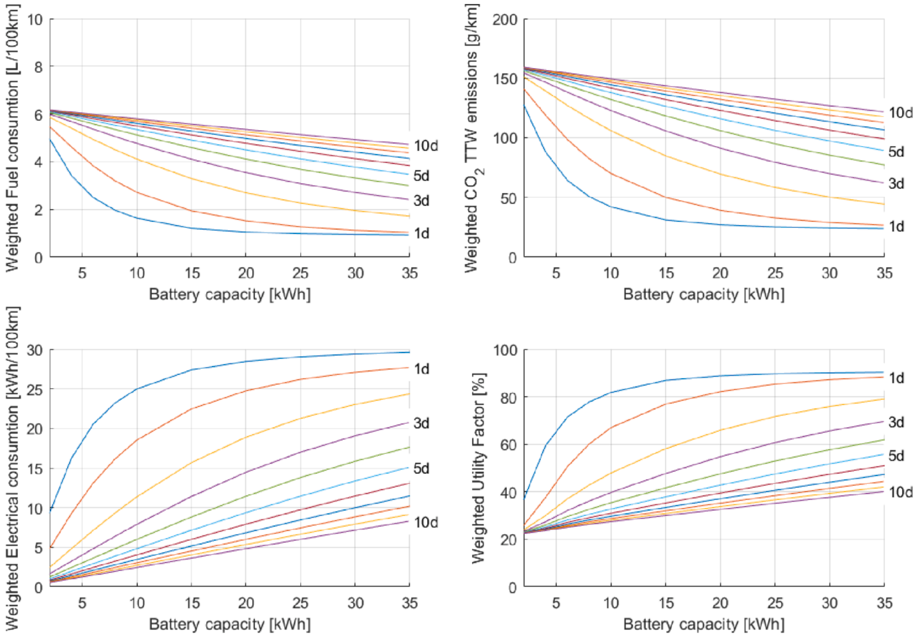

Fig. 25. Sensitivity of weighted average fuel consumption, CO_2 emissions, electrical consumption, and utility factor to the battery capacity (from 2 kWh to 35 kWh) and recharge frequency (from twice a day to every 10 days) – Diesel PHEV.

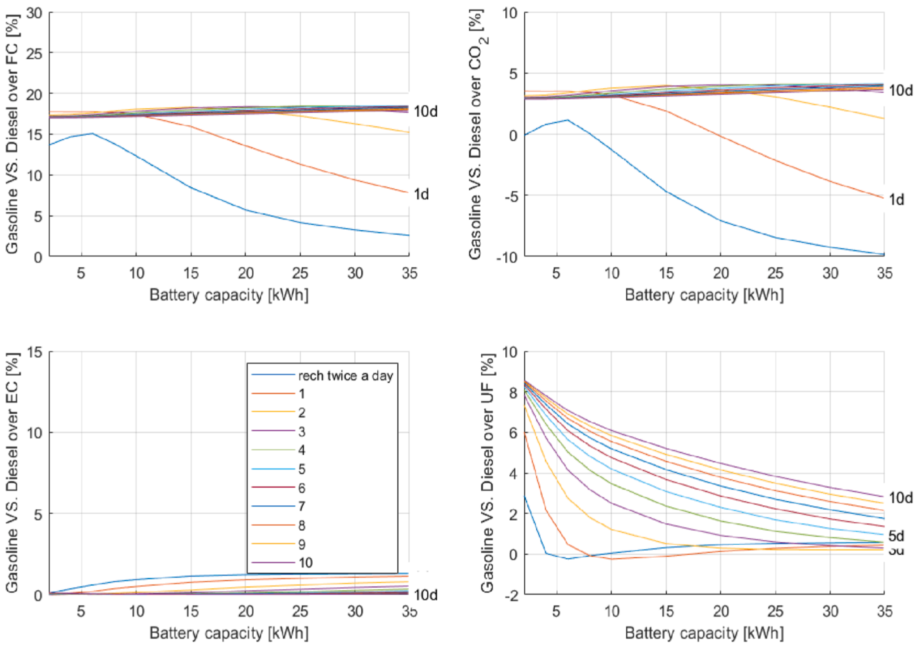

Fig. 26. Comparison between gasoline and Diesel PHEV as a function of battery sizing and recharge period.

same reasons, BEVs with smaller batteries (e.g. BEV-200) require PHEVs to have a bigger break-even utility factor.

Now is the time to bridge (Shafiei et al., 2022) results with this work: as the models developed here give the real-world utility factors as a function of the PHEV battery capacity and their recharge frequency, they can be compared to the break-even utility factor. In Fig. 31 it can be observed that a PHEV recharged every driving day or every-two driving days always has a utility factor above the break-even point, whatever the battery capacities of the PHEVs and the BEVs. This means that, under limited supply of batteries to Europe, it is always preferable to roll out PHEVs first (before BEVs) providing that they are recharged at least every-two driving days. If the PHEVs are recharged only every 5 driving days, the conclusion is somewhat different: for the PHEVs having a smaller battery (PHEV 20 and PHEV 40), the real-world utility factors are still above the break-even point. This means that "small PHEVs" (with a

Table 4
Utility Factors according to (a) (UNECE, 2017), (b) (ICCT, 2020) and (c) [this work, for a recharge frequency every day, every 2 days and every 5 days] as a function of PHEVs All Electric driving Range and battery capacity. *Relationship between PHEV AER and battery capacity according to (Shafiei et al., 2022).

PHEV AER [km] *	Battery capacity (kWh)*	UF WLTP [%] (a)	UF ICCT [%] (b)	UFRecharge/1 day [%] (c)	UFRecharge/2 days [%] (c)	UFRecharge/5 days [%] (c)
20	4.5	46	23	42	33	27
40	8.6	69	34	63	46	33
60	12.5	80	40	72	53	37
80	16.1	86	43	78	61	41
100	19.4	90	45	82	66	43

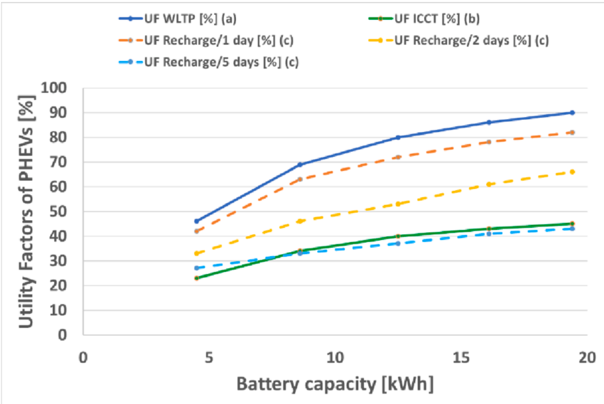

Fig. 27. Utility Factors according to (a) (UNECE, 2017), (b) (ICCT, 2020) and (c) [this work, for a recharge frequency every day, every 2 days and every 5 days] as a function of battery capacity. Relationship between PHEV AER and battery capacity according to (Shafiei et al., 2022).

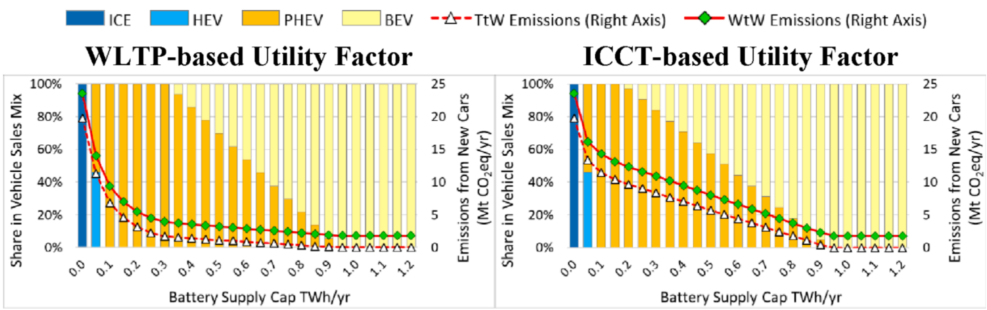

Fig. 28. Optimal vehicle sales mix minimizing WTW GHG emissions subject to constrained battery supply in 2030—Results assuming battery capacities of 1.54 kWh (HEV), and 58.4 kWh (BEV); PHEV battery capacities are optimized to minimize WTW GHG emissions, and their utility factors follow the curves shown in Fig. 27 (a) and (b). Redrawn from (Shafiei et al., 2022).

battery capacity lower than 8.6 kWh) are a no-regret option: even if they cannot be recharged very often (notwithstanding that the more often they are recharged, the better), they will always manage a deeper cut in WTW GHG emissions compared to a “BEV-only” strategy. For the PHEVs having a bigger battery (PHEV 60 to PHEV 100), the results are more contrasted if they are recharged every 5 driving days as they depend on the BEVs against which they “compete”: if the BEVs have a smaller battery (<60 kWh or 400 km driving range), they become more efficient in minimizing WTW GHG than those PHEVs; but if the BEVs batteries are bigger than 60 kWh, then the PHEVs become more efficient again, whatever their battery capacity.

5.3. Policy implications

Based on the results of this work, the policy recommendations to the EU regarding passenger cars are as follows:

- The ban on PHEVs, currently planned for 2035 according to the EU regulation, should be lifted as PHEVs are part of the optimal solution to minimize WTW GHG emissions, at least as long as there is a constraint on the supply of batteries to the EU. During the

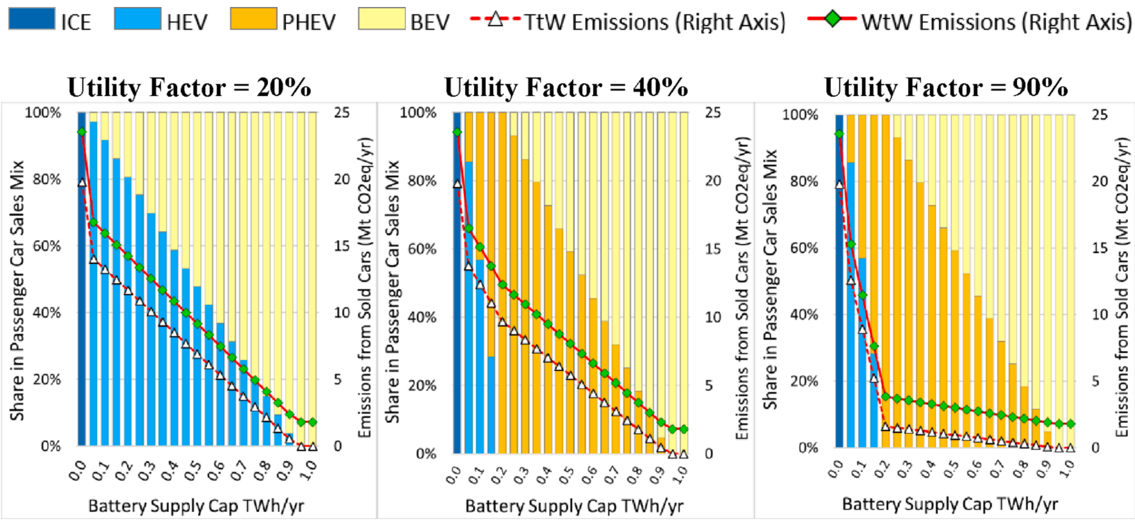

Fig. 29. Optimal vehicle sales mix minimizing WTW GHG emissions as a function of battery supply to Europe in 2030 for 3 levels of UF (20%, 40% and 90%), with break-even point being 30% — Results assuming fixed battery sizes of 1.54 kWh (HEV), 12.5 kWh (PHEV), and 58.4 kWh (BEV). Copied from (Shafiei et al., 2022).

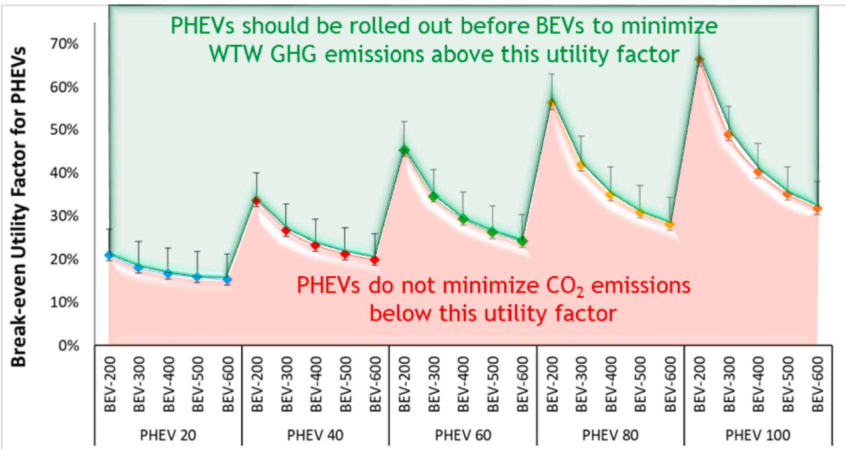

Fig. 30. Break-even utility factor of PHEVs for various combinations of battery capacities for PHEVs and BEVs. The values following "PHEV" and "BEV" relate to their All Electric driving Range. Note: error bars show the sensitivities with respect to the carbon intensity of electricity supply mix ranging from 0 to 76.4 gCO_2eq/MJ. Redrawn from (Shafiei et al., 2022).

transition, a "BEV-only" oriented strategy (omitting the contribution of PHEVs) actually results in higher GHG emissions than the optimal.

- In countries where the carbon intensity of electricity is sufficiently low (i.e. most EU countries), the regulating authority should encourage the users to recharge their PHEV as often as possible. Given the current prices of fuels and of electricity to households (i.e. home charging) in Europe, the rational behavior of users is already to recharge their PHEV as it is less expensive to operate than refueling it. Therefore there should not be any need to strongly incentivize the users to do it, as the incentive is already present in the prices. However, disincentives to recharge PHEVs should absolutely be avoided as they are counterproductive. This disincentive unfortunately exists in several EU countries, through company cars mechanisms: typically, a company car is provided with a fuel card, often leading the users to have to pay for their electricity bill when recharging at home whereas refueling is "for free" (from their point of view). Under these conditions, the users' rational behavior is to refuel rather than to recharge. This behavior is confirmed by (ICCT, 2020), which identified that the utility factor of PHEVs is significantly lower when they are company cars compared to when they are owned by individuals. This detrimental situation could partly be solved by making sure that users benefitting from a fuel card can also recharge their PHEV "for free" at home. In addition, the authorities should maximize the opportunities for the users to recharge their PHEVs, by making charging easy and accessible through a well-designed roll-out of the recharging infrastructure, for instance with more kerbside charging facilities.

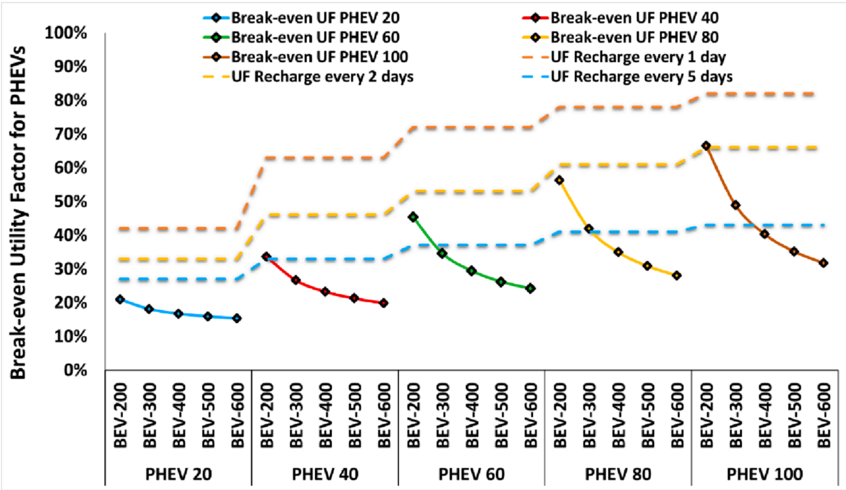

Fig. 31. Break-even utility factor of PHEVs compared to real-world utility factors for various combinations of battery capacities for PHEVs and BEVs. The values following "PHEV" and "BEV" relate to their All Electric Range. Adapted from (Shafiei et al., 2022) with additional data from this work.

- In the short term, i.e. as long as the battery supply to Europe is lower than 0.3 TWh/year and that it is impossible to make 100 % of the vehicles sales BEVs, the roll out of small PHEVs (typically with a driving range of 40 km or less) should be encouraged as they are a no-regret option on the pathway to minimizing WTW GHG emissions and optimizing the allocation of batteries to vehicles, even if recharged only every 5 driving days. In some countries or states where it is planned to ban PHEVs having a "too small" All Electric driving Range (typically<80 km), this constraint should be lifted as it prevents from properly optimizing the allocation of batteries to vehicles and minimizing WTW GHG emissions (for a given recharge frequency) during the transition.
- For PHEVs that are sold either with tax breaks or subsidies from the state (which is often the case in Europe), the authorities should have the possibility to control that PHEVs' actual utility factors are above their break-even point. It would be a way to ensure that PHEVs (and the state's money) are used for their intended use, i.e. to decarbonize transport. These controls should be particularly effective for company cars, for which the users' rational behavior is not necessarily to recharge them (as described above). For these cars which are often leased, it would be quite easy to control at the end of their leasing period that the utility factor matches with the break-even requirements. In case their utility factor is below the break-even point, a system of penalties or fines (e.g. reimbursement of the subsidies) could be considered.
- To this end, the utility factor of PHEVs should be available for consultation by the regulating authorities, with appropriate anti-tempering measures on the value displayed, and with common agreed definition and standard on the measurement of the UF.

6. Conclusions

Two Euro 6d PHEVs were selected to allow a relevant comparison between gasoline and Diesel internal combustion engines. These vehicles were tested on a chassis dynamometer and on-road, both with standard and renewable fuels, in charge depleting and charge sustaining mode.

Two simulators for the gasoline and Diesel PHEVs were set up, calibrated and validated. A Design of Experiments (DoE) was performed under various conditions (temperature, driving cycles, initial battery SoC, battery capacity) to extend the energy performance findings of these two vehicles: CO_2 emissions, Utility Factor, fuel and electrical consumptions. Finally, a simplified mathematical model was established and validated, allowing to quickly estimate these energy performance parameters for any combination of use. This work established that the energy performance of PHEVs is heavily dependent on the conditions of use (temperature, trip distance, recharging frequency, and battery sizing) as the ratio of use of each of the two energy sources available on board is extremely variable. A weighting methodology based on available real-world statistics was implemented on the parameters of ambient temperature and daily distance travelled. Furthermore, the recharging frequency and battery capacity factors, which depend on end-users and manufacturers respectively, were also varied (but not weighted as too few statistics are available), so as to provide insights via a sensitivity analysis. It shows that frequent recharging of PHEVs is a necessary condition for a high electric drive rate: recharging every day a gasoline PHEV having a battery of 15 kWh leads to an average fuel consumption of 2.25 L/100 km and a utility factor of 77 %, whilst recharging it every 3 days leads to a fuel consumption of 4.85 L/100 km (+116 %) and a utility factor of 48 % (-29 points). By comparison, the non-rechargeable gasoline HEV with a 2kWh battery evaluated under the same conditions shows an average fuel consumption of 7.3 L/100 km and a utility factor of 24 %. Compared to this reference HEV, the gasoline 15kWh PHEV allows a consumption reduction of 69 % if it is recharged every day and a reduction of 34 % if it is recharged every-three days. Furthermore, it is observed that the first kilowatt-hours of battery capacity are the most effective in electrifying the PHEVs: for instance, adding another 15 kWh of battery capacity to the vehicle, leading to a 30 kWh PHEV, would increase by only 10 points the utility factor, from 77 % to

87 %, if recharged every day; instead, the same 15 kWh battery capacity could have electrified 77 % of the mileage of another PHEV, which is more efficient if the total amount of available batteries is constrained.

(Shafiei et al., 2022) concluded that, as long as PHEVs' utility factor is above their break-even point, they are part of the optimal vehicles sales mix minimizing WTW GHG emissions in a scenario where the supply of batteries to the EU is constrained. The real-world assessment performed here confirms that, for a typical driving profile, the PHEVs' utility factors are always above the break-even point when recharged every driving day or every-two driving days. In addition, "smaller" PHEVs with an all-electric driving range of 40 km or less are always above their break-even utility factor even if recharged down to every 5 driving days.

This led to a set of policy recommendations involving the accelerated roll-out of PHEVs in the vehicles sales mix to minimize GHG emissions, instead of banning them. Possible control measures to make sure that they are used with a utility factor beyond their break-even point were also proposed.

7. Outlook: from tank-to-wheel to life-cycle emissions: a vehicle LCA interactive tool

TtW CO_2 emissions evaluated in this work do not offer a complete picture of the GHG emissions emitted during the life of a vehicle. For this, a broader analysis of the vehicle's life cycle must be determined by considering not only the TtW emissions of the vehicle during its use, but also the WtT emissions related to the energy sources (electricity and fuel productions) and finally the production and end of life of the vehicle itself, including the battery. This assessment is based on many parameters: the CO_2 intensity of electricity production, the CO_2 WtT emissions and associated biocredits of different fuel production pathways, the CO_2 emissions related to the production of the vehicles, particularly the battery, the lifetime of the vehicles, etc. Given the quantity of possible pathways, assumptions and their variability, it is most of time impossible to have consensus on the definition of a baseline (around which sensitivities can then be run). For this reason, a dynamic LCA GHG tool was developed, allowing to configure any possible combinations of parameters and to compare PHEVs life-cycle emissions with other levels of vehicle electrification: HEVs and BEVs (screenshot in Fig. 32). This tool is supported by the energy performance model developed in this article (which provides the TtW CO_2 emissions, the energies consumptions and the utility factor), to which are further connected the WtT and life-cycle emissions as a function of the selected configurations. More detail about this LCA simulator is provided in the Appendix F.

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CRediT authorship contribution statement

Roland Dauphin: Conceptualization, Methodology, Validation, Data curation, Writing – original draft, Writing – review & editing, Supervision, Project administration. **Vivien Prevost:** Conceptualization, Methodology, Software, Validation, Formal analysis, Data curation, Writing – original draft, Writing – review & editing, Visualization. **Philippe Degeilh:** Conceptualization, Methodology, Software, Validation, Formal analysis, Data curation, Writing – original draft, Writing – review & editing, Supervision. **Joris Melgar:**

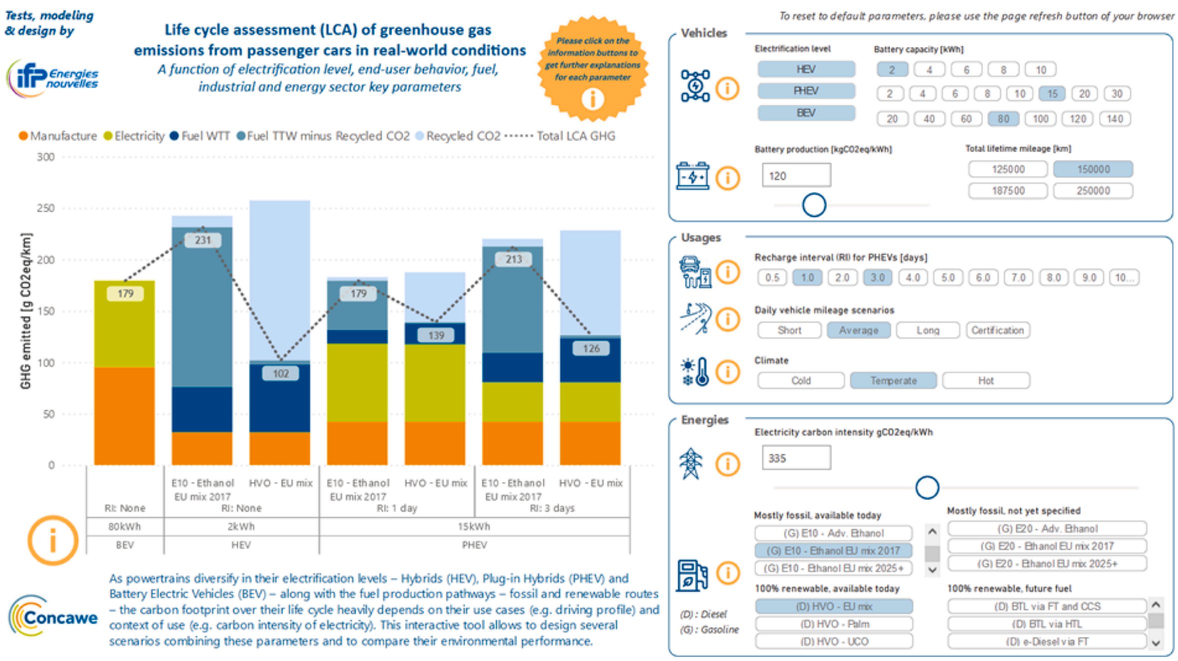

Fig. 32. Screenshot of the on-line vehicle LCA simulator (accessible at https://www.carsCO2comparator.eu).

Conceptualization, Visualization. **Corrado Fittavolini:** Validation, Writing – review & editing. **Alastair Smith:** Validation, Writing – review & editing. **Cyrille Callu:** Validation, Writing – review & editing. **Sofia Chrysafi:** Validation, Writing – review & editing. **Renate Uitz-Choi:** Validation, Writing – review & editing. **Kenneth Kar:** Validation, Writing – review & editing.

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. Supplementary material

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Glossary

AER:: All Electrical Range
Bx:: Diesel fuel containing max. x% of FAME (e.g. B7 or B10)
BEVs:: Battery Electric Vehicles
CD:: Charge Depleting
CDF:: Cumulative Distribution Function
CH4:: Methane
CO_2(eq):: Carbon Dioxide (equivalent)
COP:: Coefficient of Performance
CS:: Charge Sustaining
DOC:: Diesel Oxidation Catalyst
DoE:: Design of Experiments
Ex:: Gasoline containing max. x% v/v of ethanol (e.g. E10 or E20)
ECMS:: Equivalent Consumption Minimization Strategy
FAME:: Fatty Acid Methyl Ester
FC:: Fuel Consumption
GB:: Gearbox
GHG:: Green House Gas(es)
GPF:: Gasoline Particulate Filter
GPS:: Global Positioning System
HEV:: Hybrid Electric Vehicles
HVAC:: Heating, Ventilation and Air Conditioning
HVO:: Hydrotreated vegetable oil
ICE:: Internal Combustion Engine
LCA:: Life Cycle Assessment
LHV:: Lower Heating Value
N2O:: Nitrous Oxide
NH3:: Ammonia
NMC:: Nickel, Manganese and Cobalt
NOx:: Nitrogen Oxide
OBD:: On-Board Diagnostics
OEM:: Original Equipment Manufacturer
P2:: hybrid configuration where the electric machine is integrated between the internal combustion engine and the transmission.
PEMS:: Portable Emissions Measurement System
PHEV:: Plug-in Hybrid Vehicle
PID:: Proportional-Integral-Derivative (controller)
PM:: Particulate Matter
PMSM:: Permanent Magnet Synchronous Machine
PN:: Particulate Number
PNx:: Particulate Number with a diameter greater than x nm
RDE:: Real Driving Emissions
RED:: Renewable Energy Directive
SCR(F):: Selective Catalytic Reduction (with a soot Filter)
SoC:: State of Charge
TtW:: Tank-To-Wheels
TWC:: Three Way Catalyst
UF:: Utility Factor
VKT:: Vehicle Kilometers Travelled
WLTC:: Worldwide harmonized Light-duty Test Cycle
WLTP:: Worldwide Harmonized Light Vehicles Test Procedure
WtT:: Well-To-Tank
WtW:: Well-To-Wheels