Electrified powertrain sizing for vehicle fleets of car makers considering total ownership costs and CO2 emission legislation scenarios

Electrified Powertrain Sizing for Vehicle Fleets of Car Makers Considering Total Ownership Costs and CO_2 Emission Legislation Scenarios

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Elsevier use only: Received date here; revised date here; accepted date here

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Highlights

- Sizing electrified powertrains to be embedded in a fleet of different vehicles by the same car maker.
- Minimizing the total-cost-of-ownership of all the vehicles of the car maker in a real-world use scenario.
- Considering different present and future oriented CO2 emission regulation scenarios.
- Considering different powertrain electrification levels.
- Plug-in hybrid electrification suggested as the most promising technology for the retained car maker fleet.

Abstract

Developing effective computer-aided engineering (CAE) tools is currently a compelling need for fostering industrialization and widespread diffusion of electrified road vehicles. A CAE methodology is proposed in this paper for sizing electrified road vehicle powertrains at an overall car maker vehicle fleet level by considering different evaluation criteria involving retail price, compliance with current and future regulatory CO_2 emission requirements, drivability, and real-world operative costs. A case study is performed on a group of different vehicle models embedding the same electrified powertrain, and different vehicle electrification levels are assessed. Plug-in hybrid electric vehicle (HEV) is identified as the most robust propulsion system architecture solution considering different sizing targets and 2030 oriented regulatory scenarios. This suggests that, from the perspective of a car maker, investing in research and development and in upgrade of current vehicle production facilities to

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propose highly electrified vehicles in the market can be a more strategic and successful approach than a conservative strategy which would restrain the economic investments and limit the overall electrification level of all vehicle models. The considerably higher retail price that users are required to pay when purchasing a fleet of plug-in HEVs may in fact be paid off and eventually reveal beneficial in a long term given the avoidance of paying a regulatory CO_2 sanction and the consistent reduction in the monthly operative costs in terms of fuel and electricity. Vehicle designers can implement the presented CAE methodology for assessing electrified vehicle sizing options at the overall car maker level based on realistic use case scenarios and different potential CO_2 emission regulation scenarios.

Keywords: car maker, CO2 emissions, electrified powertrain, hybrid electric vehicle, optimal design, total cost of ownership

1. Introduction

Several research works from the literature proved the potential of fuel saving, emission reduction and economic viability of hybrid electric vehicles (HEVs) [1][2]. This has brought automotive original equipment manufacturers (OEMs) to start manufacturing and selling HEVs [3][4]. In this framework, a compelling need relates to develop computer-aided engineering (CAE) tools that can rapidly and effectively size electrified powertrains of vehicle fleets of car makers.

Fig. 1 illustrates the design space associated to HEVs from the perspective of an automotive OEM. The complete electrified vehicle OEM fleet design space can be categorized according to the powertrain architecture, the electrification level, and the number of vehicle models in the overall fleet of the car maker. As regards electrified powertrain architecture, different studies have proposed component sizing for series [5][6], parallel [7][8], power-split [9] and multimode layouts [10][11] alone. Few works have been presented as well examining few different HEV powertrain architectures at once [12]-[14].

Concerning the powertrain electrification level, research analysis and design methodologies generally focus on micro [16], mild [17][18], full or plug-in [19][20] HEVs alone. When it comes to the number of vehicle models in an OEM fleet, the reviewed literature generally considers a single vehicle type and model when designing and controlling its electrified powertrain. Nevertheless, a given propulsion system is usually developed and manufactured to be embedded in few vehicle models that are produced by the same car maker or even by different car makers. Since these vehicle models generally characterize by different values of mass, body shape and resistive load coefficients, accounting for their differences at early design stages may result beneficial in the optimization process of the propulsion system under development. Enhanced flexibility and adaptation in the operation of electrified powertrains can allow effectively embedding the same electrified propulsion system in vehicles with even more different sizes compared with conventional vehicles that are propelled by an internal combustion engine (ICE) only. A significant reduction in the number of actual power components managed by the OEM could be achieved in this way, thus bringing remarkable benefits in terms of cost and simplification. Vehicle production and assembling processes could thus be streamlined and effective simplification of the overall electrified vehicle fleet of a car maker could be attained. However, adding a further dimension in the electrified vehicle design space remarkably increases the level of complexity and the computational load associated to HEV design methodologies. As a matter of fact, significant limitations currently persist in OEM electrified vehicle fleet design concerning the variety of assessed driving conditions, the number of considered optimization criteria and the amount of retained sizing parameters at HEV powertrain level.

To answer the identified research gap, this paper introduces a CAE methodology for sizing electrified powertrains to be embedded in the overall vehicle fleet of an automotive OEM. The presented methodology is implemented in a CAE tool named Electrified Fleet Engineering Tool (EFETool). Compared with the reviewed HEV design methodologies, the EFETool introduced here can expand the design space

Nomenclature

Acronyms

AER	All electric range
AMT	Automated manual transmission
CD	Charge-depleting
DP	Dynamic programming
EAER	Equivalent all-electric range
EFETool	Electrified fleet engineering tool
EU	European Union
FD	Final drive
HEV	Hybrid electric vehicle
ICE	Internal combustion engine
IPM	Interior permanent magnet
LEZ	Low emission zone
MG	Motor/generator
OEM	Original equipment manufacturer
PHEV	Plug-in hybrid electric vehicle
RPE	Retail price equivalent
SERCA	Slope-weighted energy-based rapid control analysis
SOC	State-of-charge
TCO	Total cost of ownership
TTW	Tank-to-wheel
UDDS	Urban dynamometer driving schedule
WLTP	Worldwide harmonized light-vehicle test procedure
WTW	Well-to-wheel

Symbols

a	Vehicle acceleration
$\alpha_{CO2WTW_{electricity}}$	Weighting coefficient for well-to-wheel CO2 emitted by the electricity share
$\alpha_{CO2WTW_{fuel}}$	Weighting coefficient for well-to-wheel CO2 emitted by the fuel share
C_{ICE}	Cost of the ICE
C_{MG}	Cost of the MG, the inverter and related controller
C_{trans}	Cost of the transmission
$cost_{elec}$	Electricity cost coefficient
$cost_{fuel}$	Fuel cost coefficient
$Cost_{oper_i}$	Overall operative cost of vehicle i
$CO2_{WTW}$	Emitted well-to-wheel CO2
E_{batt_j}	Electrical energy consumption in driving mission j
E_{AC}	Total charge energy
$EAER$	Equivalent all-electric range
EE_{WLTP}	Battery electrical energy consumption in WLTP
f_j	Journey frequency of driving mission j
FC_{CD}	Fuel consumption in charge-depleting operation
FC_{CS}	Fuel consumption in charge-sustaining operation
FC_{WLTP}	Average weighted fuel consumption in WLTP
$Fine_{CO2}$	Sanction for excessive CO2 emissions
J_{OEM}	Overall OEM objective function
$kWh_{batt_{HEV}}$	Battery pack capacity
$life_{veh}$	Vehicle lifetime
m_{fuel_j}	Fuel consumption in driving mission j
M_{batt}	Battery pack mass
M_{ICE}	ICE mass
M_{MG}	MG mass
M_{trans}	Transmission mass
N_{RWC}	Number of real-world driving missions considered
N_{sales_i}	Forecasted vehicle sales
N_{veh}	Number of vehicle models of the OEM fleet
$P_{ICE_{MAX}}$	ICE maximum power
$P_{MG_{MAX}}$	MG maximum power
R_{CDA}	Charge-depleting range
R_{CDC}	Electric range
RP_i	Retail price for vehicle i
$target_{CO2_{WTW}}$	Maximum regulatory amount of CO2 emissions
ρ_{FUEL}	Fuel density
$\tau_{G,tot}$	Total transmission ratio
τ_n	Ratio of the n-gear
UF	Utility factor
φ_1	Gear ratio multiplier
φ_2	Progression factor
z	Total number of gears

exploration for HEVs by effectively considering several vehicle models of an automotive OEM, rather than a single vehicle. Additional key novelties brought by this paper in the field of electrified powertrain design include:

- The exhaustive consideration of both start-stop vehicles, mild HEVs, full HEVs and plug-in HEVs (PHEVs).
- The rapid simulation of HEV fuel economy and well-to-wheel CO2 emission reduction capabilities both in current homologation procedures and real-world driving missions.
- The minimization of the total cost of ownership (TCO) at the overall car maker fleet level in terms of retail price, fuel cost, electricity cost and eventual fines for excessive well-to-wheel CO2 emissions.
- A sensitivity analysis of the changes in the identified best electrified fleet propulsion system design according to different sizing criteria and to several present and 2030 oriented CO2 emission legislation scenarios.

Considering a fleet of different electrified vehicle models manufactured by a car maker, the aim of this paper is finding the best powertrain sizing option considering fuel and electrical energy economy, drivability, and total cost of ownership for the overall OEM fleet. In this framework, the following research and technological questions are addressed:

- From a car maker perspective, is investing in advanced vehicle electrification technologies more convenient than paying the CO2 emission fines involved in present and future legislation scenarios?
- Is the higher retail price of plug-in HEVs economically viable in terms of TCO over different time horizons from an overall car maker fleet perspective?
- Does the suggested electrified powertrain sizing option change when different cost targets are considered (e.g. retail price plus CO2 emission fine, TCO in real-world driving conditions over different durations of ownership)?
- Does the suggested electrified powertrain sizing option change when different CO2 emission legislation scenarios are considered?

The paper is structured as follows. The general workflow of the design methodology implemented in EFETool is introduced first. Regulations and homologation procedures for CO2 emissions of road vehicles find then discussion. These lay the foundation for evaluating the economic impact of HEV design on an OEM according to the forecasted sanctions related to the compliance with CO2 emission limits. The objective function which needs minimization in EFETool at the automotive OEM level is then introduced. A case study to demonstrate the effectiveness of the proposed EFETool is then

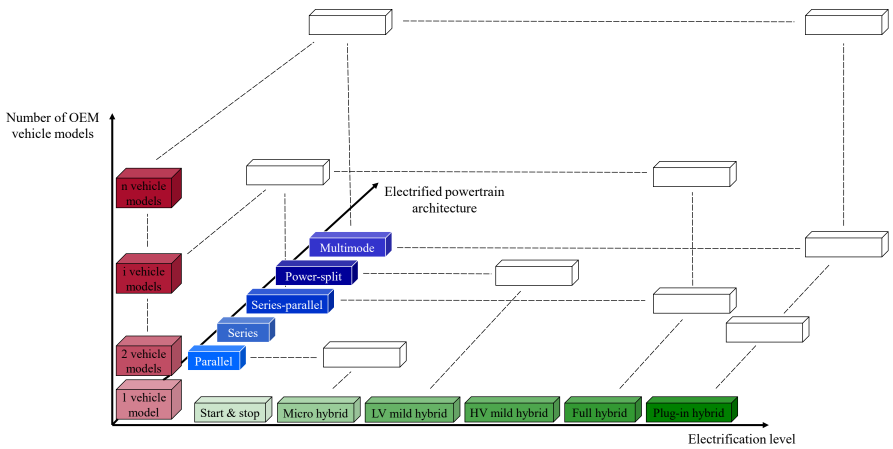


Fig. 1. Design space associated to HEVs from the perspective of an automotive OEM.

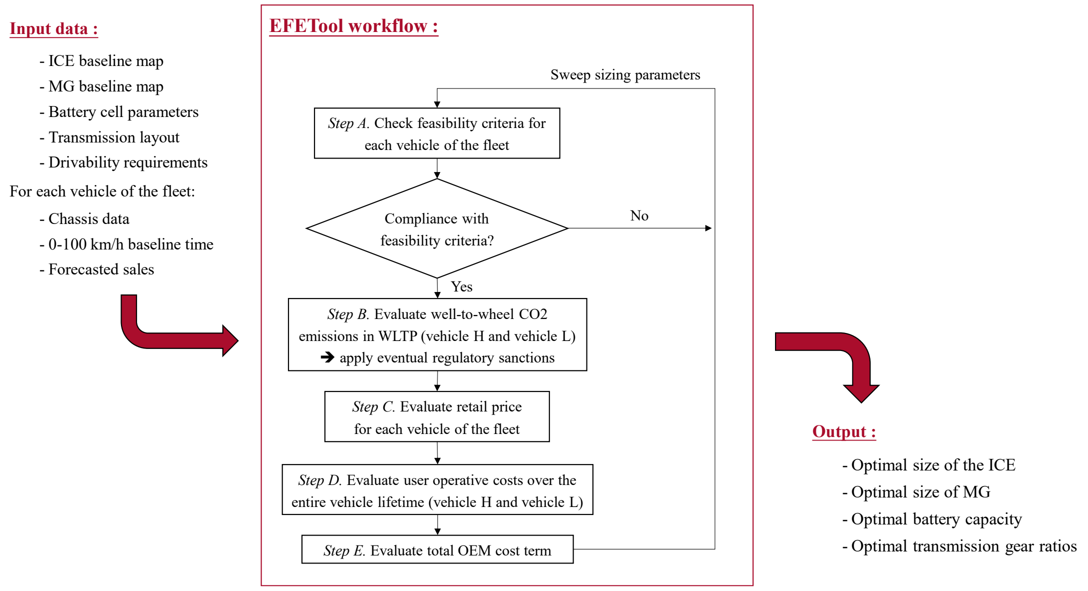


Fig. 2. Workflow of the implemented CAE tool for sizing electrified road vehicle fleets of car makers.

performed designing a parallel P2 hybrid electric propulsion system to be embedded in a number of different vehicles belonging to an OEM fleet while considering different regulatory scenarios both at present, in the short-term future and in the long-term future. Conclusions are finally summarized.

2. Workflow of the Electrified Fleet Engineering Tool

Fig. 2 illustrates the workflow of EFETool including required input data and outcomes of the CAE tool. Required input data relate to baseline data for:

- the electrified driveline architecture. For example, considering stepped gear transmission HEVs, this involves defining the position of the electric motor/generator (MG) and the number of gears;
- the ICE fuel map;
- the electrical loss maps of all the MGs to be included in the electrified transmission layout;
- the feasibility requirements which the vehicles of the considered OEM fleet are requested to fulfill;
- 0-100 km/h acceleration time associated to the baseline conventional vehicle version for each vehicle of the retained fleet;
- chassis data for each vehicle of the retained fleet (including for example mass, road load coefficients, wheel dynamic radius);
- the forecasted sales for each vehicle of the retained fleet.

A brute force exploration approach is initially implemented here in considering all the possible options included within a discretized design space for the OEM electrified fleet powertrain. At each iteration, a given electrified powertrain design option is selected and its evaluation process starts. In step A in Fig. 2, the compliance with the feasibility requirements imposed by the user is initially verified for each vehicle of the retained fleet in terms of drivability and gradeability. In positive case, the workflow is continued and the next evaluation step is carried out. On the other hand, the present design candidate is discarded and the following option is evaluated if at least one of the feasibility criteria is not fulfilled by at least one vehicle of the fleet. The well-to-wheel CO2 emissions are then computed in the worldwide harmonized light-vehicle test procedure (WLTP) according to the implemented HEV off-line energy management strategy, which it will be recalled later in section 2.2. Estimating the potential well-to-wheel CO2 emission reduction for the given electrified powertrain design option allows computing the eventual economic sanctions as required by current and forecasted future legislations. The retail price for each vehicle of the OEM fleet is then evaluated at step C of the illustrated workflow according to the values of sizing parameters selected for the given electrified powertrain candidate design. Step D consequently involves estimating the operative costs over the entire vehicle lifetime both in terms of fuel and electricity by considering various real-world driving missions and payload conditions. Operative costs for each vehicle of the fleet can be predicted in this way according to the implemented off-line HEV energy management strategy. Once these steps are performed, the overall OEM cost term for the vehicle fleet embedding the given electrified powertrain candidate design can be finally computed. The EFETool workflow can then be iterated for the next HEV design option until all the candidates of the design space have been evaluated. After all the design options have been assessed, EFETool returns as output the optimal solution for the electrified powertrain to be embedded in the fleet of vehicles in terms of size of the ICE, size of the MGs, battery capacity and transmission gear ratios.

Detailed description for each step of EFETool illustrated in Fig. 2 will be carried out in the follow-up of this paper, starting from the feasibility constraints for HEV sizing options.

2.1. Feasibility constraints for HEV sizing options

This sub-section illustrates the feasibility constraints which need fulfillment when deciding upon the acceptability of a given electrified powertrain design option. Retained feasibility constraints particularly include gradeability requirements, drivability requirements and, in the case of PHEVs, all electric range (AER) requirements. As concerns drivability and gradeability requirements, specific criteria which need compliance by all the vehicles of the considered fleet are reported in Table 1. Tests number 1 to number 4 in Table 1 have been retained from [21]. However, an adaptation of road slope values for tests number 3 and number 4 has been performed to replicate typical requirements of A-segment and B-segment passenger cars. Test number 5 finally requires each vehicle embedding the given electrified powertrain design option to perform a 0-100 km/h full throttle maneuver in equal or less time compared with the baseline conventional vehicle as earlier defined by the user as input to EFETool.

Table 1

Gradeability and drivability requirements at Step A of EFETool

Test number	Road slope	Requirement
1	30%	Perform a standing start
2	0%	Maintain vehicle speed at 150 km/h
3	7%	Maintain vehicle speed at 80 km/h
4	0%	Capability to charge-sustain the battery at 130 km/h
5	0%	Perform a 0-100 km/h full throttle maneuver in equal or less time compared with the baseline conventional vehicle

A further category of feasibility criteria considered in EFETool for PHEV sizing options relate to the AER. Since European Union (EU) air quality limit values related to particulate matter are still being exceeded in many cities, more than 200 low emission zones (LEZs) have been instituted in 12 EU countries [22][23]. LEZs generally restrain the access to vehicles associated to low tailpipe emission capabilities (i.e. battery electric vehicles and PHEVs). A research trend has consequently arisen in the field of optimal on-line PHEV energy management strategies that enable pure electric driving through forthcoming LEZs and minimize the overall fuel consumption [24][25]. In this framework, a suitable value of AER, i.e. the spatial distance that the vehicle can cover without producing tailpipe emissions, should be guaranteed at an early design stage by an appropriate sizing of the battery capacity. Since LEZs are generally established in cities, the urban dynamometer driving schedule (UDDS) is considered in this work as representative of the driving conditions which a PHEVs would likely to encounter in LEZs. Then, an appropriate value of AER can be set as requirement for each PHEV sizing candidate analyzed. In this work, the value of 30 kilometers is selected as the distance to be covered in pure electric driving in an urban scenario represented by steady repetitions of the

UDDS without depleting the battery state-of-charge (SOC) below its minimal allowed value as per battery specifications. When a given electrified powertrain design option exhibits a sufficiently high value of battery capacity to enable PHEV operation, this AER requirement is included in the feasibility criteria to be mandatorily satisfied in EFETool.

With reference to Fig. 2, feasible design candidates are then assessed in terms of well-to-wheel CO2 emissions in WLTP. However, a suitable HEV energy management strategy requires recalling first in the next sub-section in order to enable the comprehensive evaluation of each electrified powertrain design option while accounting for both smooth driving constraints and battery state boundaries.

2.2. Estimating electrified vehicle fuel and electrical energy economy

A fundamental step in EFETool involves estimating the fuel and electrical energy economy capability of a given electrified powertrain sizing candidate. This can be achieved by performing a simulation of a backward numerical model of the HEV embedding the electrified powertrain candidate layout and executing a given driving mission over time. Off-line control algorithms are implemented to this end that exploit the knowledge of the entire driving mission in advance to find the optimal electrified powertrain control trajectories in terms of overall fuel and electrical energy consumptions [26][27]. Implemented HEV control algorithms must take into account battery state constraints and smooth driving criteria when finding the optimized HEV control trajectories [28][29]. For an HEV equipped with an automated manual transmission (AMT), this could correspond to limit the overall frequency of ICE de/activations and gear shifts over time for example. Control trajectories are thus identified that are closer to real-world HEV powertrain operation and that can be more easily replicated in an actual vehicle [30][31].

As it will illustrated in detail later, the design space for the electrified vehicle fleet design problem is remarkably large and comprises more than tens of thousands of possible candidates. Since several homologation cycles and long-distance real-world driving missions need to be simulated for each sizing candidate, computational efficiency is a compelling need when estimating the ideal fuel and electrical energy economy of the electrified vehicles. To answer this need, the author of this paper has introduced a rapid near-optimal HEV control algorithm named slope-weighted energy-based rapid control analysis (SERCA). The capability of SERCA to effectively generate near-optimal charge-sustaining HEV control trajectories while preserving computational efficiency and accounting for smooth driving constraints was extensively demonstrated in [32] by benchmarking with the global optimal performance predicted by DP. Recently, the effectiveness and computational rapidness of SERCA have been proved when predicting the optimized charge-depleting operation of PHEV powertrains as well [33]. Thanks to the implementation of SERCA, the optimized HEV operation with smooth driving constraints can be predicted within few minutes even when considering long-distance real-world driving missions (i.e. that last more than 2 hours). These considerations led to implement SERCA as control strategy to predict HEV fuel and electrical energy economy in EFETool. To this end, a backward HEV powertrain numerical model is implemented. The considered HEV numerical model evaluates speeds and torques of power components from the requirements of the driving mission, while steady state fuel table and loss maps are retained for modelling the ICE and the MGs, respectively. The interested reader can consult [32] for more details regarding the HEV modelling and control approaches.

3. Regulatory evaluation of HEV CO2 emissions

In this section, an overview of the regulatory evaluation of CO_2 emissions is presented. The homologation test procedure for given conventional vehicles, HEVs and PHEVs is particularly recalled first. The methodology for measuring the emitted well-to-wheel CO_2 at the overall fleet level of a given car maker is then described.

3.1. Homologation test procedure in WLTP

Starting from 2018 September 1, WLTP has replaced the new European driving cycle as drive cycle for the official assessment of the compliance of new

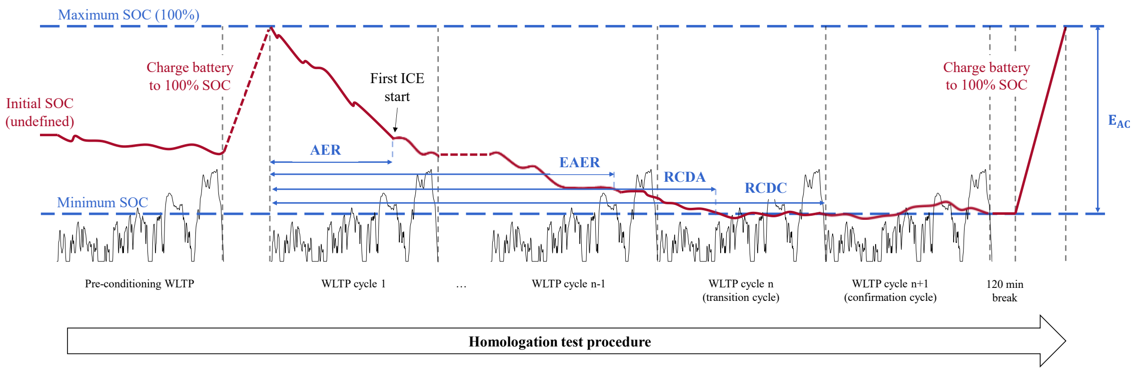


Fig. 3. Schematic overview of the homologation test procedure for PHEVs in WLTP.

road vehicles with the CO_2 emission targets in European Union. As far as conventional vehicles, mild HEVs and full HEVs are concerned, the evaluation of CO_2 emissions can be carried out by considering the WLTP performed only one time. Particularly for HEVs, the assessment of potential tailpipe emissions reduction can be performed through numerical simulations by imposing similar values of battery SOC at the beginning and the end of the drive cycle. On the other hand, when it comes to PHEVs, a more articulated methodology is set out in the homologation test procedure which is illustrated in Fig. 3 and described as follows [34].

The procedure begins with a pre-conditioning WLTP cycle given an initial undefined value of battery SOC. Subsequently, the battery is fully charged to 100% SOC and the tested vehicle is placed in a climate-controlled area at 23°. The WLTP cycle is then repeated for several times until the battery SOC reaches its minimum operating value set by the manufacturer and the PHEV powertrain operating mode switches from charge-depleting (CD) to charge-sustaining. From a measurement and mathematical point of view, this condition corresponds to the net energy change in the battery from the beginning to the end of the given WLTP cycle being less than 4% of the WLTP cycle energy at the wheels [35]. The WLTP cycle in which this condition is achieved is called *confirmation cycle* (i.e. WLTP *n+1* in Fig. 3), while the previous cycle (i.e. WLTP *n* in Fig. 3) is referred to as the *transition cycle* since it involves the shift from charge-depleting operation to charge-sustaining operation. A 120-minute break follows the completion of the confirmation cycle, and the battery is then charged to the maximum SOC level while measuring the total charge energy E_{AC}.

Once the illustrated workflow for the homologation test procedure is completed, the average weighted fuel consumption in WLTP FC_{WLTP} in liters per a hundred kilometers can be evaluated using eq. (1):

$$FC_{WLTP} = UF \cdot FC_{CD} + (1 - UF) \cdot FC_{CS} \quad (1)$$

where FC_{CD} and FC_{CS} stand for fuel consumption values in liters per 100 kilometers in charge-depleting operation and in charge-sustaining operation, respectively. Charge-depleting operation is particularly carried out throughout the actual charge-depleting range (i.e. R_{CDA} in Fig. 3). UF is the utility factor which can be defined as function of the electric range R_{CDC}, i.e. the distance driven up to and including the transition cycle. The tabulated value of UF set out by EU regulations as function of R_{CDC} is illustrated in Fig. 4.

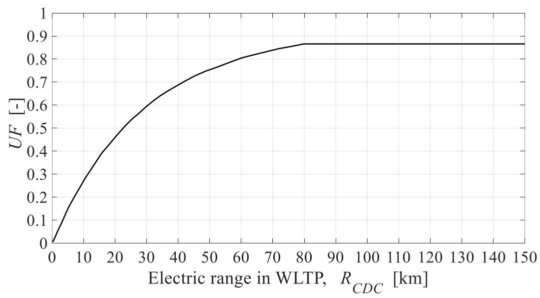


Fig. 4. WLTP utility factor in the EU as a function of the electric range.

As far as the high-voltage battery is concerned, its electrical energy consumption EE_{WLTP} in kilowatt-hours per kilometer can be determined by dividing the total charge energy at the end of the test procedure E_{AC} by the equivalent all-electric range (EAER) as follows:

$$EE_{WLTP} = \frac{E_{AC}}{EAER} \quad (2)$$

where the EAER can be calculated by considering the total driven distance up to and including the transition cycle n (i.e. R_{CDC}) and removing the time instants in which the ICE was set to operate.

The definition of the average weighted fuel consumption as a function of the utility factor may bring into question the specific PHEV charge-depleting operation which can minimize the registered value of regulatory fuel consumption. In particular, achieving the right balance between extending the R_{CDC} by activating the ICE in charge-depleting operation (i.e. performing an optimized charge-depleting operation) and lowering the specific contribution of fuel consumption in charge-depleting operation (FC_{CD}) may not be trivial. Both these options of charge-depleting operation should thus be evaluated in EFETool for the PHEV sizing candidates in order to retain the best alternative. An example can be presented by retaining the parallel P2 HEV powertrain and vehicle data presented in [33] (i.e. an A-segment 1045.6kg passenger car, a 51kW ICE, a 28kW MG, and a 5-speed AMT). A 9.12kWh battery pack is considered in this case featuring 1200 A123 ANR26650M1-B cells. Different charge-depleting strategies have been simulated considering the PHEV controlled off-line using SERCA by varying the number of WLTP cycles performed in charge-depleting operation until the transition cycle is reached. This corresponds to set the same value of net depletable battery energy in SERCA (i.e. considering the battery fully charged), and then vary the number of cascaded WLTP cycles to be included in the simulated driving mission. A further WLTP cycle is then simulated in charge-sustaining operation to account for the confirmation cycle and to evaluate FC_{CS}. Three different charge-depleting control cases have been particularly retained performing respectively 1, 2 and 3 WLTP cycles in charge-depleting operation before switching to charge-sustaining operation in the confirmation cycle. The battery SOC is constrained in this case not to attain lower values than 20% in charge-sustaining operation. Obtained results in terms of EE_{WLTP}, R_{CDC}, UF, FC_{CD}, FC_{CS}, and FC_{WLTP} are compared in Table 2, while Fig. 5 illustrates the SOC trajectories obtained using SERCA for all the three control cases. In this example, switching from charge-depleting to charge-sustaining operation after one WLTP cycle would not be beneficial since a significant amount of electrical energy is still available

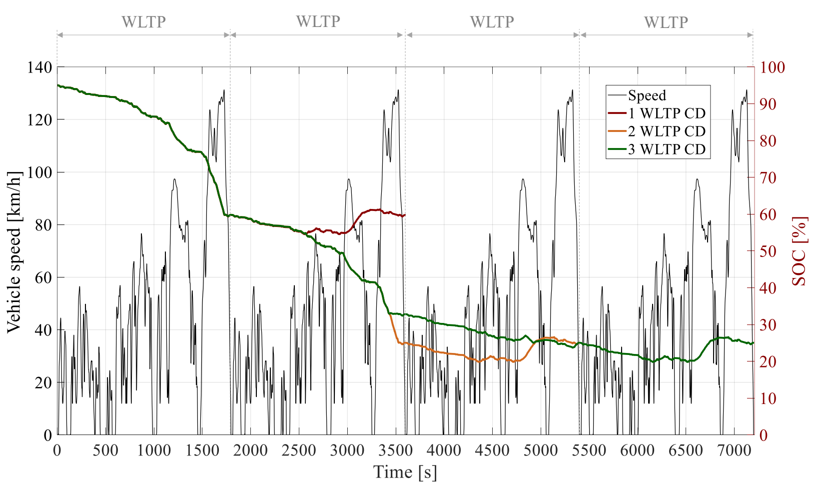


Fig. 5. Battery SOC trajectories in WLTP over different charge-depleting operations (i.e. 1 WLTP cycle in CD, 2 WLTP cycles in CD, 3 WLTP cycles in CD) for a parallel P2 PHEV using SERCA as HEV control strategy.

Table 2

Results in terms of electrical energy consumption and fuel consumption over different charge-depleting (CD) operation scenarios for a parallel P2 PHEV

Number of WLTP cycles performed in CD operation			
	1	2	3
EE_{WLTP} [kWh / 100km]	0.14	13.50	11.77
R_{CDC} [km]	23.26	46.52	69.79
UF [-]	0.51	0.73	0.84
FC_{CD} [L/100 km]	0.00	0.00	1.40
FC_{CS} [L/100 km]	4.40	4.40	4.40
FC_{WLTP} [L/100 km]	2.15	1.17	1.89

in the battery (i.e. corresponding to a SOC value of around 60%). On the other hand, compared to 1 WLTP cycle in charge-depleting operation, completing 2 WLTP cycles in charge-depleting operation allows to double the value of R_{CDC} and consequently increase the UF from 0.51 to 0.73. This allows lowering the value of the average weighted fuel consumption FC_{WLTP} by around 46% without increasing the value of FC_{CD} (that is still zero). When performing 3 cycles in charge-depleting operation, the UF can be extended up to 0.84, thus increasing the weight for the fuel consumption in charge-depleting mode and potentially decreasing the weighted value of fuel consumption FC_{WLTP}. Nevertheless, in this case the suggested improvement in FC_{WLTP} for the 3 charge-depleting WLTP cycles strategy is not able to balance the considerable increase in the value of fuel consumption in charge-depleting operation FC_{CD}. A weighted value of fuel consumption FC_{WLTP} higher by around 61% is therefore obtained in this case with respect to the 2 charge-depleting WLTP cycles strategy. When accounting for fuel consumption only, a PHEV operation similar to a CD-CS strategy would therefore be preferred in this case compared to a blended charge-depleting strategy as a result of the definition of UF as the weighting parameter. However, each charge-depleting strategy should be evaluated for each sizing option under analysis in order to identify the most suitable operation as a function of the corresponding battery capacity and electrified powertrain layout. This feature finds therefore implementation in EFETool by exploiting the computational rapidness of SERCA as near-optimal off-line energy management strategy for PHEV sizing options.

In the next sub-section, the methodology for evaluating the overall well-to-wheel CO_2 emissions at an OEM fleet level from the values of FC_{WLTP} and EE_{WLTP} for single vehicles will be illustrated.

3.2. Determining the CO_2 emission of overall OEM fleets

The recent introduction of WLTP has not only changed the homologation drive cycle for new vehicles, yet it laid the foundations for re-thinking the overall emission evaluation procedure at the OEM vehicle fleet level. Particularly in EU regulations, the entire commercially available vehicle fleet of a car maker needs to be divided in several CO_2 interpolation families [36]. The CO_2 interpolation families (also called road load families) are groups of vehicles produced by the same car manufacturer which not necessarily have the same vehicle shape and body, yet they are distinguished by the following common features:

- The characteristics of the embedded ICE (e.g. fuel type, engine displacement, method of aspiration);
- The characteristics of the embedded transmission, including the type (e.g. manual, automatic) and the model (e.g. number of gears, number of clutches, gear ratios);
- The number of powered axles;
- The Ambient Temperature Correction Test (ATCT), which in turn involves thermal and after-treatment systems (e.g. cooling system, catalytic converter);
- The vehicle class, which can be defined as function of the power-to-mass ratio (PWr) measured in kW/Tonne;
- The operation strategy of all CO_2 mass emission influencing components, which in turn involves the electrical share of the powertrain as example, including the MGs, the high-voltage battery and the power electronics among the other components.

Each interpolation family of the overall fleet of a car maker can thus be evaluated separately. Within the same interpolation family, vehicles can then be sorted according to the WLTP road load energy demand as illustrated in Fig. 6. In this context, vehicle-L and vehicle-H denote the vehicle in the family with the

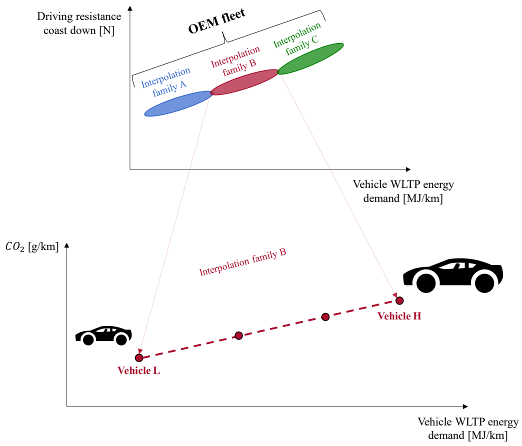


Fig. 6. Interpolation families in an overall car maker fleet.

Table 3

Definition of tested vehicle mass for vehicle-L and vehicle-H of an interpolation family

Parameter	Vehicle-L	Vehicle-H
Curb weight	▪ Fuel level ≥ 90% tank ▪ Usual set of tools ▪ Spare wheel ▪ Liquids	▪ Fuel level ≥ 90% tank ▪ Usual set of tools ▪ Spare wheel ▪ Liquids
Optional equipment	No optional equipment	~150 kg
Tested vehicle mass	Curb weight + 100 kg + 15% maximum payload	Curb weight + 100 kg + 15% maximum payload + Optional equipment

lowest energy demand and the one with the highest energy demand, respectively. When performing the homologation test procedure, different values of payload are defined by EU regulations for vehicle-L and vehicle-H, as it has been summarized in Table 3. The mass for vehicle-L in WLTP is particularly represented by the curb weight with the addition of 100 kg and 15% of the maximum vehicle payload, while an additional equipment of around 150 kg is included as well for vehicle-H.

After each test procedure is completed as described in sub-section 3.1, the total well-to-wheel CO_2 emitted by the tested vehicle in grams per kilometer $CO2_{WTW}$ can be determined following eq. (3).

$$CO2_{WTW} = FC_{WLTP} \cdot \rho_{FUEL} \cdot \frac{\alpha_{CO2WTW\,fuel}}{100} + EE_{WLTP} \cdot \frac{\alpha_{CO2WTW\,electricity}}{100} \quad (3)$$

ρ_{FUEL} is the fuel density in grams per liter, while $\alpha_{CO2WTW\,fuel}$ and $\alpha_{CO2WTW\,electricity}$ denote weighting coefficients for the well-to-wheel CO_2 emitted by the fuel share and the electricity share, respectively. The coefficient $\alpha_{CO2WTW\,fuel}$ is expressed in grams of CO_2 per grams of fuel and accounts for the fuel production, distribution and retail processes among the others. On the other hand, $\alpha_{CO2WTW\,electricity}$ is expressed in grams of CO_2 per kilowatt-hour of battery energy and stands for the contribution of CO_2 emitted by the electricity production and distribution. Especially this latter coefficient may considerably depend on the mix of primary sources used for producing the electricity.

Once the homologation test procedure has been performed for both vehicle-L and vehicle-H and their corresponding values of $CO2_{WTW}$ have been determined, the well-to-wheel CO_2 emitted by the remaining vehicles in the considered road load family can be determined according to EU regulations through linear interpolation in the plot with WLTP road load demand and emitted CO_2 as independent variables, as it has been illustrated in Fig. 6 and in [36]. This methodology allows assigning a value of $CO2_{WTW}$ for all the vehicles of an interpolation family without exhaustively performing experimental tests on each single vehicle. Determining the amount of the eventual fine that the OEM needs to pay for each vehicle not complying with CO_2 emission limits established by EU regulations is made possible in this way in step B in the workflow illustrated in Fig. 2. More details about the determination of the value of the overall OEM objective function will be provided in the next section.

4. Objective function determination

This section discusses the determination of the total OEM objective function which needs minimization within the car maker electrified fleet design process. In addition to the eventual fine applicable when the CO_2 emission requirements are not met, the remaining two terms of the OEM objective function relate here to the overall vehicle retail price and to the vehicle operative cost. These are respectively computed in Step C and Step D in the EFETool workflow illustrated in Fig. 2. In this section, specific methodologies for evaluating vehicle retail price and operative cost will be described. Then, the definition of the OEM objective function as a combination of the single evaluating parameters will be discussed.

4.1. Vehicle retail price

The methodology for determining the retail price of each vehicle model for a given sizing option for the car maker fleet under analysis is described in this sub-section by defining the vehicle production cost first. The overall vehicle production cost is assumed here to include cost terms related to single components or vehicle sub-systems such as:

- The ICE;
- The MG and the related inverter and controller;
- The transmission;
- The vehicle chassis;
- The high-voltage battery pack;
- The high-voltage charging system (in the case of PHEVs);
- The vehicle accessories.

Production costs for each of these items have been retained from literature. In case costs were reported in US dollars in the research works consulted, these have been converted into euros using the October 2020 conversion ratio of 0.85€/1$ [37].

The ICE cost C_{ICE} has been defined as a linear function of its maximum mechanical power $P_{ICE_{MAX}}$ expressed in kW. Values for the cost coefficients have been retained from FASTSim [38], which in turn have been derived from [39]:

$$C_{ICE}\left(P_{ICE_{MAX}}\right) = 12.33\,\frac{€}{kW} \cdot P_{ICE_{MAX}} + 452\text{ €} \quad (4)$$

The MG, inverter and related controller overall cost C_{MG} has been defined as a linear function of the MG maximum mechanical power $P_{MG_{MAX}}$ as well. Values for the corresponding cost coefficients have been derived as follows from a forecast for a long-term scenario involving interior permanent magnet technology conducted in [39]:

$$C_{MG}\left(P_{MG_{MAX}}\right) = 13.60\,\frac{€}{kW} \cdot P_{MG_{MAX}} + 327\text{ €} \quad (5)$$

The transmission cost C_{trans} has been determined as follows as a linear function of the ICE maximum mechanical power as expressed in [40]:

$$C_{trans}\left(P_{ICE_{MAX}}\right) = \alpha_1 \cdot \alpha_2 \cdot P_{ICE_{MAX}} \quad (6)$$

with α_1 equal to 1 considering compact vehicles, and α_2 equal to 6.87€/kW for a 5-gears transmission layout.

The vehicle base cost (including chassis, wheels and other components) has been estimated being 8,500€ and 10,800€ for class-A passenger cars from [40] and for class-B passenger cars from [41], respectively.

The production cost for additional components including accessories, the tank, the accessory battery and the starter is estimated being 238€ for a start-stop conventional vehicle and 276€ for an HEV from [40].

In case of PHEVs, two additional costs of respectively 360€ (to account for an on-board charger and cables) and 255 € (to account for the installation of a home charger) have been retained from [41].

The production cost for the HEV high-voltage battery pack as a function of its capacity is assumed being 280€/kWh following the value for 2018 resulting from [41].

In order to finally determine the overall vehicle retail price, an OEM retail price equivalent (RPE) multiplier of 1.5 is retained in this case from [42] and applied to the production cost of each described vehicle sub-system except for the vehicle base cost. The overall retail price RP_i for generic vehicle model i of the design option for the car maker fleet under analysis can be computed in this way.

4.2. Vehicle operative cost

Step D in the EFETool workflow illustrated in Fig. 2 involves estimating the operative costs for the overall vehicle lifetime. In this work, the vehicle operative costs are modeled comprising only the fuel cost and the electricity cost where applicable. To this aim, a vehicle use scenario needs dedicated definition based on various parameter. The first one relates to the driving missions which the vehicle should perform in its daily operation. Nine real-world driving missions recorded by global positioning system in the northern

Italy area are particularly considered in this work as reported in the Appendix. Fig. 12 illustrates vehicle speed profiles and road altitude profiles over time for each of the nine real-world driving missions, while Table 10 reports related statistics concerning journey distance, travel time, vehicle speed, vehicle acceleration and road slope as example. RWC01 and RWC02 particularly involve downhill and uphill driving conditions, respectively, accompanied by some extra-urban and highway driving. They were recorded in Langhe, a hilly area in Piedmont, northern Italy. RWC03 considers urban driving conditions solely and it was recorded in the city of Torino, northern Italy. RWC04 refer to a journey around 72 kilometers long that includes different driving conditions such as urban, extra-urban, highway, uphill and downhill. RWC05 considers urban driving conditions recorded in the city of Turin. RWC06 and RWC09 are long distance driving missions (i.e. respectively around 140 km and 51 km long) which are mostly performed in highway driving conditions. Finally, both RWC07 and RWC08 have been recorded in mountain areas and involve remarkable road altitude difference between the starting point and the ending point of the driving mission. RWC07 is representative of down-mountain driving conditions involving around 630m geographical descent with frequent braking due to a series of hairpin turns followed by an extra-urban driving section. On the other hand, RWC08 involves quite constant up-mountain driving achieving a remarkable overall geographical ascent of around 1430m.

Overall, the considered recorded missions aim at representing a realistic variety of driving conditions. A complete and realistic vehicle use scenario should also consider the time frequency at which each driving mission is performed, and a typical vehicle payload level associated to the specific driving mission. In this work, the time frequency for the generic driving mission j is denoted as f_j and it is expressed as the number of times per month in which the given driving mission is performed. As far as the payload level is concerned, a linear ranking ranging from 1 to 5 has been established respectively corresponding to lightly loaded vehicle weight (i.e. curb weight plus an 80kg driver and related baggage) and full loaded vehicle (i.e. corresponding to the maximum payload allowed by the car manufacturer depending on the vehicle characteristics). Table 4 reports values of parameters for journey frequency and payload level for all the considered real-world driving missions. The resulting vehicle use scenario has been assumed in this dissertation based on personal experience and on the observation of common family passenger car usage in urban areas in northern Italy. As example, RWC03 is assumed being performed around twice a day with light payload conditions to account for daily urban commuting between home and workplace. Similarly, the short distance urban journey corresponding to RWC05 is assumed being performed at a considerable time frequency over the month. On the other hand, highway long driving missions are assumed being performed less frequently (i.e. once a month) at different payload conditions. The journey frequency has been further decreased considering more extreme driving missions such as RWC07 and RWC08, which are assumed being performed once every four months at fully loaded vehicle weight simulating family vacations as example. Overall, the considered vehicle use scenario retains around 970km of travel length per month.

Table 4

Journey frequency and payload level for the real-world driving missions of the considered vehicle use scenario

	Journey frequency (Number of times/month)	Payload level (1÷5)
RWC01 - Downhill	4	3
RWC02 – Uphill	4	3
RWC03 – Urban01	60	1
RWC04 – LongExtraUrban	4	4
RWC05 – Urban02	16	4
RWC06 – LongHW01	1	4
RWC07 – Downmountain	0.25	5
RWC08 – Upmountain	0.25	5
RWC09 – LongHW02	1	2

In EFETool, each driving mission of the retained vehicle use scenario is simulated twice considering respectively vehicle-L and vehicle-H carrying the given mission payload and embedding the electrified powertrain design option under analysis. SERCA is implemented as HEV control strategy. Regarding micro HEVs (i.e. start-stop conventional vehicle powertrain layouts), the gear to engage is selected at each time instant based on the instantaneous fuel consumption minimization and by applying a gear shifting minimization strategy similar to the SERCA one in order to comply with the maximum allowed overall number of gear shifts. Once fuel consumption and eventual electrical energy consumption have been determined for both vehicle-L and vehicle-H, the corresponding consumption values for the remaining vehicles of the OEM fleet can be evaluated by interpolating in the road load family as function of the driving mission energy demand as described in sub-section 3.2. Finally, the estimated overall operative cost for a given vehicle model *i* of the considered OEM fleet $Cost_{oper_i}$ is expressed in equation (7).

$$Cost_{oper_i} = \left[\sum_{j=1}^{N_{RWC}} \left(\frac{m_{fuel_j}}{\rho_{FUEL}} \cdot cost_{fuel} + E_{batt_j} \cdot cost_{elec}\right) \cdot f_j \right] \cdot life_{veh} \quad (7)$$

N_{RWC} is the number or real-world driving missions considered Equal to 9 in this case). m_{fuel_j} and E_{batt_j} are the optimized fuel consumption (in grams) and electrical energy consumption from the grid (in kilowatt-hours) evaluated in the retained driving mission *j*, respectively. $cost_{fuel}$ stands for the cost coefficient for fuel and amounts to 1.59 euro per liter following the average Italy gasoline price in the third quarter of 2019 [43]. $cost_{elec}$ is the cost coefficient for electricity and amounts to 0.0799 euro per kilowatt-hour following the average Italy electricity price in the second semester of 2019 [44]. On its behalf, $life_{veh}$ is the vehicle lifetime expressed in the number of months. Concerning start-stop conventional vehicles, mild HEVs and full HEVs, $Cost_{oper_i}$ considers the fuel consumption contribution only as they don't exploit electricity coming from the grid. On the other hand, both fuel and electricity contributions are retained in the energy consumption of PHEVs. In this case, two simulations are particularly performed for each driving mission considering two different battery SOC conditions at the beginning of the journey, i.e. battery charged to the maximum allowed SOC and battery already operating in charge-sustaining mode (i.e. assuming that no electrical energy coming from the grid is available in the battery pack). Both m_{fuel_j} and E_{batt_j} are then evaluated by giving 75% of weight to the simulation considering the battery charged to the maximum allowed SOC at the beginning of the driving mission, and 25% of weight to the simulation that neglects the contribution of electricity coming from the grid. This assumption takes into account two main factors. On one hand, PHEV users have been found considerably engaged with exploiting the possibility to on-board store electricity from the grid and use it as primary energy source for propulsion [45][46]. On the other hand, uncertain development of public charging infrastructure may currently restrain the capability of charging the battery pack through the grid before the beginning of each journey [47][48].

Once the operative cost over the entire vehicle lifetime has been determined in this way for each vehicle of the interpolation family under consideration, the entire OEM objective function which needs minimization in EFETool can be evaluated as it will be described in the next sub-section.

4.3. Defining the OEM objective function

The overall OEM objective function J_{OEM} which needs minimization in EFETool to find the best powertrain design option for the electrified fleet under analysis is discussed in this sub-section. The analytical expression of J_{OEM} id obtained by including the single cost terms calculated in the previous sub-sections and it is reported in eq. (8).

$$J_{OEM} = \sum_{i=1}^{N_{veh}} \{RP_i + Fine_{CO2} \cdot \max\left[\left(CO2_{WTW} - target_{CO2_{WTW}}\right), 0\right] + Cost_{oper_i}\} \cdot N_{sales_i} \quad (8)$$

N_{veh} stands for the number of different vehicle models for the OEM fleet under analysis. RP_i is the retail price for the vehicle model *i* as computed in sub-section 4.1, while $Cost_{oper_i}$ is the estimated vehicle operative cost over its entire lifetime as evaluated in eq. (7). $CO2_{WTW}$ is the total well-to-wheel CO_2 emitted in WLTP by the tested vehicle in grams per kilometer as obtained from equation (3), while $target_{CO2_{WTW}}$ stands for the maximum amount of CO_2 that the considered vehicle type can emit according to the regulatory requirements. $Fine_{CO2}$

represents the regulatory sanction applied by the European Commission in case the legislated CO_2 emission requirements are not met. From 2019 on, the sanction $Fine_{CO2}$ particularly amounts to 95 euros for each CO_2 g/km above the limit set [49]. Finally, N_{sales_i} is the number of units predicted to be sold for the vehicle model *i* and it can be determined according to historic data or market forecasts. Thanks to this coefficient, more emphasis is given in the overall OEM objective function to the vehicle models that are forecasted having a larger number of units sold. Following the illustrated procedure, the OEM objective function can thus be expressed as a combination of different terms aiming at accommodating the needs of both the car maker and the vehicle daily users. The car maker can particularly reduce the well-to-wheel CO_2 emissions of the overall vehicle fleet, thus minimizing the impact of regulatory sanctions on its yearly budget or even avoiding being penalized. On the other hand, users may be encouraged to purchase and drive low emission vehicles characterized by a reduced TCO represented by the sum of the retail price and the operative costs in terms of fuel and electricity from the grid. In the next section, a case study will be described to demonstrate the capability of the developed EFETool to rapidly size the electrified powertrain for a vehicle fleet of a car maker.

5. Case study: CAE of an OEM vehicle fleet using EFETool

The operating principle and the workflow of the developed EFETool have been described in the previous sections of this paper. On its behalf, this section is dedicated to performing a case study that illustrates the potential of implementing the described CAE tool to optimally size the electrified powertrain for a car maker vehicle fleet. Retained data for an interpolation family of an OEM fleet and considered sizing parameters will be presented first. A variety of regulatory scenarios that are assumed coming into place both in the near term and in the long term will then be detailed to properly account for different legislative requirements in the overall OEM objective function. Finally, obtained results will be outlined.

5.1. Retained OEM data

Table 5 lists the vehicle data for the car maker fleet retained in this study. The considered interpolation family features four passenger cars of which two models (VehA and VehB) are class A vehicles and two models (VehC and VehD) are class B vehicles. Values for curb weight, maximum payload, wheel dynamic radius, 0-100 km/h acceleration time $t_{0-100km/h}$ and baseline maximum ICE power $P_{ICE_{MAX}}$ have been directly retained from the website of the car manufacturer. On the other hand, road load data have

Table 5
Vehicle data for the retained OEM fleet

	VehA	VehB	VehC	VehD
Vehicle class	A	A	B	B
Curb weight [kg]	835	980	1150	1245
Maximum payload [kg]	500	500	500	600
Wheel dynamic radius [m]	0.2764	0.2890	0.3013	0.3002
RL_A [N]	104.49	89.50	95.06	139.67
RL_B [N/(m/s)]	2.428	2.504	3.352	2.622
RL_C [N/(m/s)^2]	0.41	0.454	0.331	0.462
$t_{0-100km/h}$ [s]	13.8	14.7	12.4	14.9
Baseline $P_{ICE_{MAX}}$ [kW]	51	51	70	70
N_{sales}	178,284	184,027	84,789	37,266

been retained from the US EPA database [50] while the number of forecasted units sold N_{sales} has been considered from historic data for the corresponding vehicles.

Despite the baseline conventional vehicle versions of the retained OEM vehicles embed ICEs characterized by different values of maximum power (specifically 51kW and 70kW), more uniformity is aimed to be reached through EFETool by having all vehicles embedding the same electrified powertrain. Enhanced flexibility and increased available tractive power concerning electrified propulsion systems may be exploited in this way to reduce the number of different components manufactured or purchased in total from the car maker. Consistent advantages may be achieved from the OEM perspective in terms of streamlining the manufacturing process and reducing the number of different parts managed, thus laying the foundations for easing development and mass production processes of more complex powertrains such as the electrified ones. Dedicated on-board real-time HEV energy management strategy may then be developed that can achieve predefined targets for each specific vehicle model (e.g. fuel consumption minimization, peculiar driving performance enhancement).

5.2. Retained HEV sizing parameters

The HEV powertrain architecture considered in EFETool for this case study is represented by a parallel P2 layout featuring a 5-speed transmission and a gear ratio connecting the MG output shaft to the gearbox input shaft, as illustrated in Fig. 7. Totally six sizing parameters can be identified in this case that allow determining the best powertrain option to be embedded in the retained car maker fleet. These relate to (1) the ICE size, (2) the battery pack capacity, (3) the MG size, (4) the differential gear ratio, (5) the gear ratio between MG output shat and gearbox input shaft, and (6) the overall ratio between first gear ratio and fifth gear ratio of the transmission.

The ICE size can be particularly varied by linearly scaling the ICE fuel map and maximum torque curve according to the specific value of $P_{ICE_{MAX}}$ under analysis. This case study particularly considers the 3 cylinders in-line spark ignition 51kW ICE considered earlier in this paper, with the baseline fuel map is illustrated in [33]. The battery pack capacity can be modified by varying the number of embedded cells. The baseline cell is represented by the A123 ANR26650M1-B type which has been considered in [51]. Similarly to the ICE, the MG size can be modified by linearly scaling the corresponding electrical loss map and the maximum torque curves. Three different MGs are retained in this study for the baseline data of electric machines respectively for PHEV, full HEV and mild HEV layouts under analysis. The corresponding operating maps have been generated here using Amesim® software [52] and they refer to an 8kW 48V interior permanent magnet (IPM) machine suitable for mild HEVs, a 36kW 230V IPM machine suitable for full HEVs, and a 79KW 360V IPM machine suitable for PHEVs, respectively.

Gear ratios for the differential and the mechanical coupling between MG output shaft and gearbox input shaft can be easily changed as simple parameters. Once the total transmission ratio $\tau_{G,tot}$ has been set as sizing parameter, i.e. the ratio between first gear ratio τ_1 and final gear ratio τ_z, the intermediate gear ratios can be computed following progressive gear steps. The related equations are reported in eq. (9) [53]:

$$\varphi_1 = \sqrt[z-1]{\frac{1}{{\varphi_2}^{0,5(z-1)(z-2)}}\tau_{G,tot}} \; ,$$
$$\tau_{G,tot} = {}^{\tau_1}/_{\tau_z} \; , \tau_n = \tau_z {\varphi_1}^{(z-n)} {\varphi_2}^{0,5(z-n)(z-n-1)} \tag{9}$$

where z is the number of gears (equal to 5 in this case), φ_2 is the progression factor (equal to 1.1 in this case study) , and τ_n is the gear ratio of the n-gear.

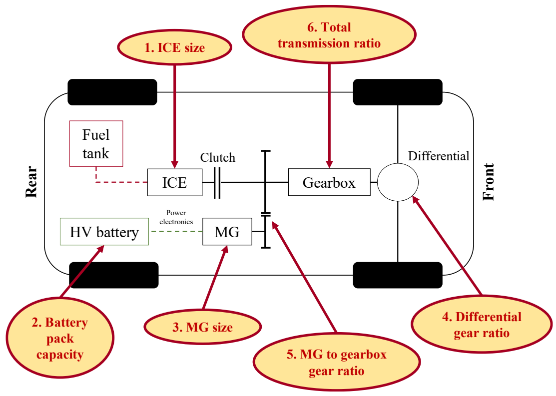


Fig. 7. Sizing parameters retained in EFETool for a parallel P2 stepped gear transmission HEV powertrain layout.

Once values of sizing parameters have been set for the powertrain option under analysis, a dedicated procedure is implemented in EFETool to scale the vehicle mass depending on the selected parameter values. The considered mass scaling approach is described in the next sub-section.

5.3. HEV mass scaling

The mass scaling procedure implemented in EFETool aims at updating the mass values for specific components of the electrified powertrain under analysis according to selected values of sizing parameters. Mass values for the ICE, the MG, the transmission and the battery are particularly updated for each sizing candidate.

The ICE mass M_{ICE} in kilograms has been defined as a linear function of its maximum mechanical power $P_{ICE_{MAX}}$ expressed in kilowatts. Values for the cost coefficients have been retained from FASTSim [38]:

$$M_{ICE}\left(P_{ICE_{MAX}}\right) = 0.47\frac{kg}{kW} \cdot P_{ICE_{MAX}} + 61\ kg \quad (10)$$

Similarly, the MG mass M_{MG} in kilograms has been defined as a linear function of its maximum mechanical power $P_{MG_{MAX}}$ expressed in kilowatts. Values for the cost coefficients have been retained from [39]

$$M_{MG}\left(P_{MG_{MAX}}\right) = 0.532\frac{kg}{kW} \cdot P_{MG_{MAX}} + 21.6\ kg \quad (11)$$

The mass of the transmission M_{trans} has been assumed linearly depending on the ICE maximum mechanical power:

$$M_{trans}\left(P_{ICE_{MAX}}\right) = 0.64\frac{kg}{kW} \cdot P_{ICE_{MAX}} \quad (12)$$

where the value for the multiplicative coefficient has been retained from [40] for a 5-speed transmission layout.

The mass of the battery pack M_{batt} for a mild and full HEV sizing options has been defined as linear function of the overall pack capacity $kWh_{batt_{HEV}}$ expressed in kilowatt-hours:

$$M_{batt}\left(kWh_{batt_{HEV}}\right) = \frac{kWh_{batt_{HEV}} \cdot 10^3}{90.9\frac{Wh}{kg}} \quad (13)$$

where the value for the multiplicative coefficient has been derived considering li-ion technology from [54]. Following the same reference, a similar approach has been implemented for battery packs of PHEV sizing options as well:

$$M_{batt}\left(kWh_{batt_{PHEV}}\right) = \frac{kWh_{batt_{PHEV}} \cdot 10^3}{140\frac{Wh}{kg}} + 35\ kg \quad (14)$$

Where the additional 35 kilograms allow accounting for the housing that protects the battery pack in case of crash [55].

5.4. Retained regulatory scenarios

Different CO_2 emission regulatory scenarios are considered in EFETool for this cases study in order to assess the sensitivity in selecting the best powertrain design option depending on current and future regulations. Each regulatory scenario can be distinguished according to three main parameters, i.e. $\alpha_{CO2WTW_{fuel}}$, $\alpha_{CO2WTW_{electricity}}$ and the regulatory CO_2 emission limit. $\alpha_{CO2WTW_{fuel}}$ and $\alpha_{CO2WTW_{electricity}}$ have been particularly defined in sub-section 3.2 and used in eq. (3) as weighting coefficients for the well-to-wheel CO_2 emitted by the fuel share and the electricity share, respectively. Seven different regulatory scenarios are considered in this case study with corresponding values for key parameters summarized in Table 6.

Scenarios no.1 (2020TTW) and no.2 (2020WTW) consider the 2020 EU CO_2 regulations involving a fleet-wide average emission target of $95 g_{CO2}/km$ [49]. Scenario no.1 considers tank-to-wheel CO_2 emissions only by setting to 0 the CO_2 contribution from the use of electricity as performed in current type approval procedures that neglect well-to-tank emissions [56]. On the other hand, scenario no. 2 accounts for the overall WTW CO_2 emission of the road vehicle and thus considers the contribution from generation, distribution, and retail processes for the electricity as well. Values for $\alpha_{CO2WTW_{fuel}}$ and $\alpha_{CO2WTW_{electricity}}$ for both these regulatory scenarios have been retained from [57] and represent an average of corresponding estimates for all the European countries. On their behalf, scenarios no.3 to no.7 consider regulatory emission limits in 2030. Scenarios no. 3 (2030CETTW) to no. 5 (2030FEWTW) particularly

Table 6

Values of weighting coefficients for the WTW CO2 emitted by the fuel share and the electricity share according to the considered regulatory scenarios

	Regulatory scenario code	$\alpha_{CO2WTW_{fuel}}[\frac{g_{CO_2}}{g_{fuel}}]$	$\alpha_{CO2WTW_{electricity}}[\frac{g_{CO_2}}{kWh_{batt}}]$	Regulatory CO_2 emission limit $[\frac{g_{CO_2}}{km}]$
1	2020TTW	3.15	0	95
2	2020WTW	3.75	508	95
3	2030CETTW	3.15	0	81
4	2030CEWTW	3.75	508	81
5	2030FEWTW	3.75	238	81
6	2030CESR	3.75	508	59
7	2030FESR	3.75	238	59

consider the fleet-wide average emission target of 81g_{CO2}/km which is set to come into force in 2030 by current regulations [49]. On the other hand, scenario no.6 (2030CESR) and scenario no.7 (2030FESR) contemplate stricter regulations for 2030 that in the future will set the fleet-wide average emission target to 59g_{CO2}/km as forecasted in [58]. Scenario no.3 considers tank-to-wheel CO_2 emissions only as it has been performed in scenario no.1. Scenario no. 4 (2030CEWTW) and scenario no.6 involve a value of $\alpha_{CO2WTW_{electricity}}$ that has been estimated in literature according to the mix of primary sources used for producing the electricity in the second decade of this century. On the other hand, scenario no.5 and scenario no.7 assume a decrease in the well-to-wheel CO_2 emission contribution of electricity thanks to the widespread diffusion and increased usage of cleaner primary sources for producing the electricity (e.g. renewable sources). The value of $\alpha_{CO2WTW_{electricity}}$ has been decreased in this case to 238 g_{CO2}/kWh_{batt} following the related estimation performed in [59].

In the next sub-section, obtained results for each of the described regulatory scenarios will be discussed.

6. Results

In order to perform an OEM electrified powertrain optimization following the procedure illustrated for EFETool, the design space needs generation first. This relates here to set possible values for the P2 HEV sizing parameters illustrated in Fig. 7, particularly corresponding to the ones reported in Table 7. Six, ten and ten different sizes are retained for the ICE, the MG and the battery pack, respectively. As concerns transmission parameters, three different values are considered for $\tau_{G,tot}$ and the FD ratio, while four values are retained for the MG to gearbox ratio. This leads to a design space comprising totally 21,600 different sizing possibilities processed through the developed EFETool.

Within the illustrated sizing space, conventional vehicles correspond to a value of 0 for both the MG power and the battery capacity, mild HEVs relate to the 0.65kWh battery pack options featuring either 8kW or 15kW MGs. On the other hand, full HEV sizing candidates correspond to the 1.12kWh and the 1.69kWh battery pack options embedding either the 16kW MG or the 28 kW MG. Finally, PHEV sizing options relate to an MG maximum power and a battery

Table 7

Swept values of sizing parameters for the EFETool case study

Sizing parameters	Swept values
$P_{ICE_{MAX}}$ [kW]	[36 ; 47 ; 58 ; 69 ; 81 ; 92]
$P_{MG_{MAX}}$ [kW]	[0 ; 8 ; 15 ; 16 ; 28 ; 29 ; 57 ; 85 ; 112 ; 140]
Battery capacity [kWh]	[0 ; 0.65 ; 1.12 ; 1.69 ; 2.9 ; 4.02 ; 5.18; 7.51 ; 9.8 ; 12.16]
MG to gearbox ratio	[0.5 ; 1; 2.25 ; 4]
$\tau_{G,tot}$	[4.00 ; 4.67 ; 5.34]
FD ratio	[2.6 ; 3.4 ; 4.2]

pack capacity equal to or greater than 29kW and 2kWh, respectively.

Results obtained for this EFETool case study are reported in the following up of this section. Particularly, examples of average results for a single vehicle of the entire car maker electrified fleet are illustrated in terms of retail price, monthly fuel cost and monthly electricity cost as function of the ICE power, the MG power and the battery pack capacity in Fig. 8. Moreover, regulatory CO_2 emissions over different legislative scenarios are shown in Fig. 9. For the ease of graphical representation, the considered six-dimension sizing space has been reduced to a three-dimension sizing space in these plots by including the best transmission sizing options for each single set of ICE power, MG power and battery pack capacity. In the three-dimension sizing space illustrated, sizing candidates explored through the brute force approach in EFETool are shown as black squares, while a linear interpolation has been performed to illustrate the rest of the sizing space as

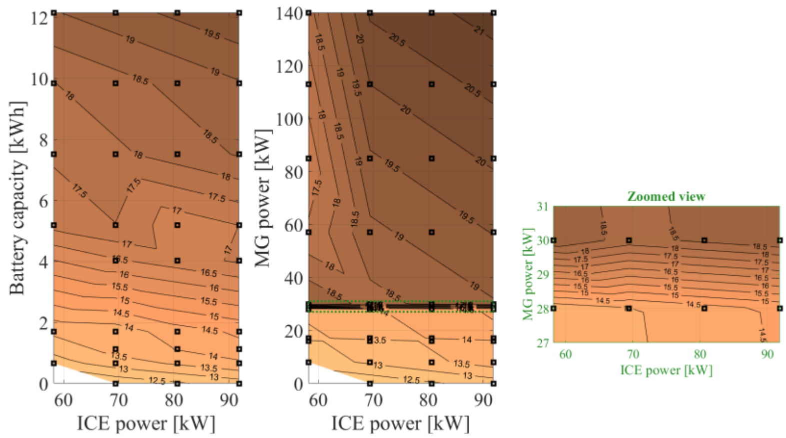
well in the continuum. In this context, unfeasible candidates do not appear in the sizing space illustrated. Finally, Fig. 10 illustrates regulatory CO2 emissions of the optimal P2 HEV powertrain sizing options identified and the related legislative limits over the considered regulatory scenarios. In the following up of this sub-section, a sensitivity analysis of the obtained results in terms of retail price, monthly operative costs and regulatory CO_2 emissions will be performed first. Then, optimal identified sizing options will be discussed according to the regulatory scenarios considered and different optimization targets.

6.1. Sensitivity analysis for retail price, operative cost and regulatory CO_2 emissions

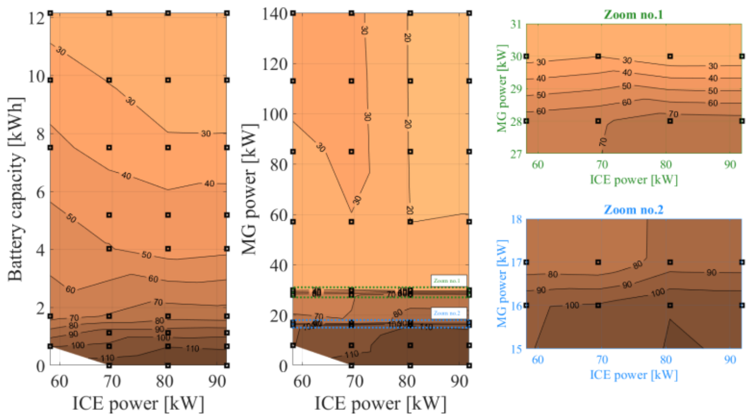
Fig. 8(a) illustrates how the average retail price for the vehicles of the OEM fleet may be slightly influenced by the ICE size at lower degrees of electrification, while considerable higher sensitivity can be observed with respect to the battery pack capacity and the MG size. These two latter parameters can indeed induce a variation in the average vehicle retail price of around 10,000€ within the considered sizing space. Moreover, an abrupt variation in the average retail price can be observed in the right sub-plot of Fig. 8(a) in correspondence with the MG size of around 30kW, which can be attributed to the shift from full HEV to PHEV sizing options entailing additional costly components such as the on-board charger and the home charger as example.

Fig. 8(b) and Fig. 8(c) highlight how the average monthly fuel cost and the average monthly electricity cost respectively decrease and increase from lower to higher degrees of electrification. However, the average monthly fuel cost overcomes the corresponding electricity cost by one to two orders of magnitude throughout the sizing space considered. As example, monthly fuel costs of around 120€, 100€ and 70€ can be achieved on average for conventional vehicle, mild HEV and full HEV sizing options through an appropriate choice of the retained sizing parameters, while remarkably lower fuel costs can be achieved through the adoption of PHEV sizing options (i.e. up to around 15€ per month). On the other hand, the monthly electricity cost for PHEV sizing options never exceeds 15€ further highlighting the economic convenience of the usage of electricity from the grid to propel the vehicles.

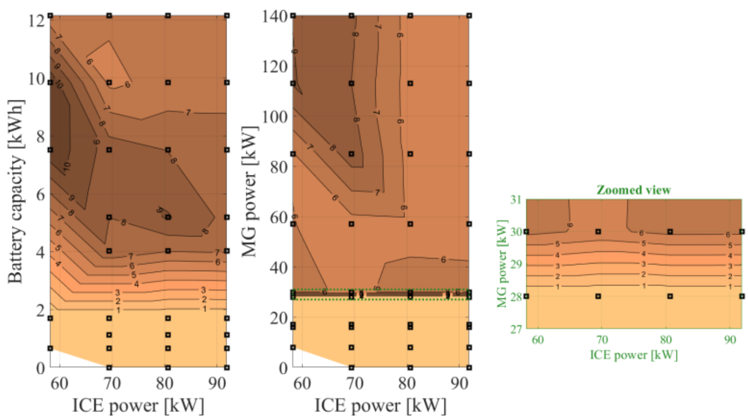
Concerning the average regulatory CO_2 emissions, Fig. 9(a) suggests how standardized tailpipe emissions can be set to 0 in WLTP for the TTW legislative scenarios through an appropriate choice of sizing candidates. On the other hand, CO_2 emissions for conventional vehicle, mild HEV and full HEV sizing candidate respectively exceed 150g/km, 130g/km and 110g/km, thus involving the forced payment of a regulatory fine for not respecting the CO_2 emission limits. By including the consideration of well-to-tank (WTT) emissions as well in the standardized CO_2 emissions, the corresponding values shown in Fig. 9(b) and Fig.9(c) for different WTW scenarios increase to more than 170g/km, 150g/km and 130g/km for conventional vehicle, mild HEV and full HEV sizing candidate, respectively. As concerns PHEV sizing options, regulatory CO_2 emissions range from around 60g/km to around 120g/km for legislative scenarios involving current electricity mix of primary sources used for producing the electricity as shown in Fig. 9(b). This suggests that the limit of 59g/km related to a conservative prediction of a tightness on the 2030



(a) Average retail price [k€] as a function of the ICE power, the MG power and the battery pack capacity



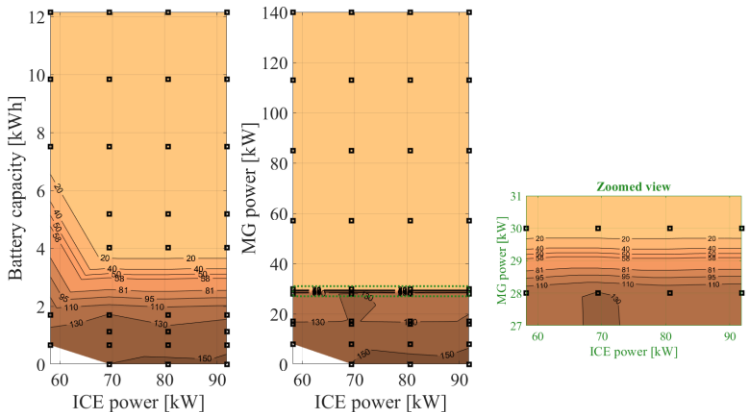
(b) Average monthly fuel cost [€] as a function of the ICE power, the MG power and the battery pack capacity



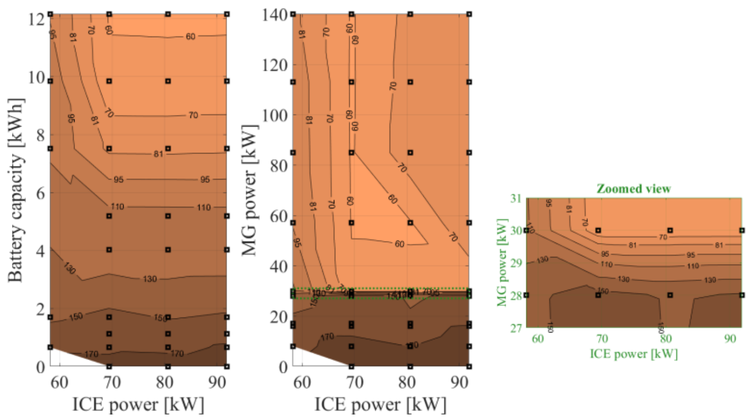
(c) Average monthly electricity cost [€] as a function of the ICE power, the MG power and the battery pack capacity

Fig. 8. Results obtained using EFETool for the 2020TTW scenario in terms of average retail price, average monthly fuel cost and average monthly electricity cost considering the overall electrified fleet of the car maker.

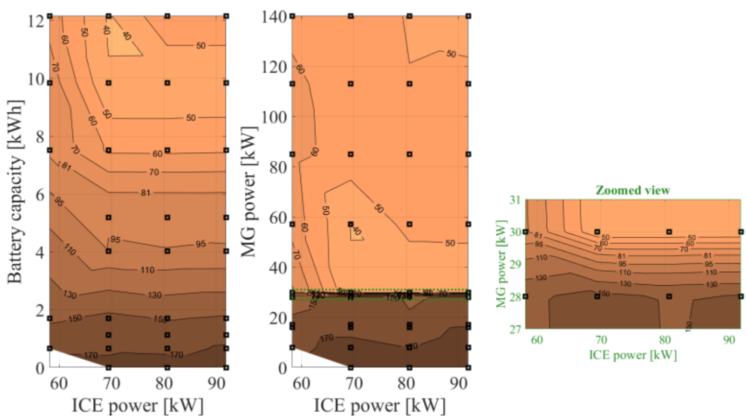
CO_2 emission regulations may nearly be complied by



(a) 2020TTW and 2030CETTW scenarios



(b) 2020WTW, 2030WTW and 2030CESR scenarios



(c) 2030FEWTW and 2030FESR scenarios

Fig. 9. Average regulatory CO2 emissions in g/km for the vehicles of the overall electrified fleet of the OEM as function of the ICE power, the MG power and the battery pack capacity.

PHEV sizing options even with the current electricity

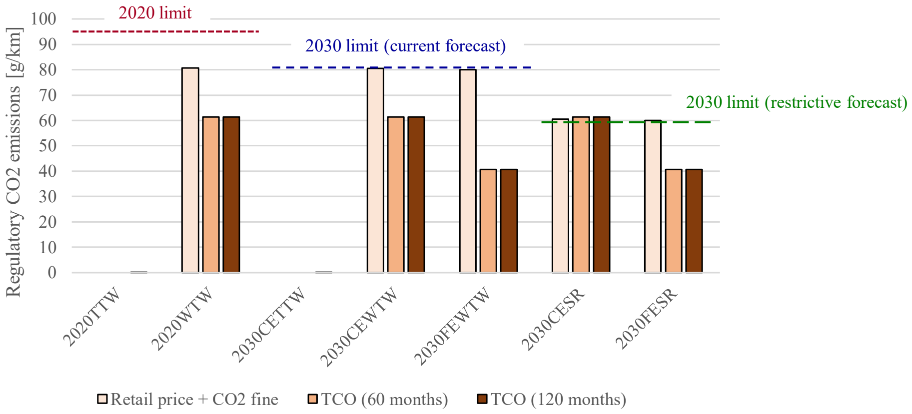


Fig. 10. Average regulatory CO2 emissions of the optimal P2 HEV powertrain sizing options and related legislative limits for the considered OEM electrified fleet over different optimization targets and regulatory scenarios.

mix of primary production sources, as further illustrated in Fig. 10 and detailed in the next paragraph for the identified optimal sizing options. However, by lowering the CO_2 emitted by the electricity coming from the grid through the usage of cleaner primary sources, the regulatory CO_2 emissions may further decrease ranging from around 40g/km to around 100g/km as shown in Fig. 9(c).

6.2. Optimal electrified powertrain sizing options

Table 8 and Table 9 respectively report optimal P2 HEV powertrain sizing options and related cost terms and energy performance over the considered regulatory scenarios and sizing optimization targets such as (1) retail price and CO_2 fine, (2) TCO over 60 months of vehicle lifetime (i.e. around 58,000 km of vehicle lifetime) and (3) TCO over 120 months of vehicle lifetime (i.e. around 116,000 km of vehicle lifetime). On the other hand, Fig. 11 illustrates a breakdown of the average vehicle cost terms for the optimal P2 HEV powertrain sizing options identified over different optimization targets and regulatory scenarios. In general, all the optimal sizing options identified over the different regulatory scenarios and optimization targets are of PHEV type and embed the same MG size (i.e. corresponding to 29kW), while different and specific values of the remaining sizing parameters are obtained as it will be discussed below. This demonstrates how current and upcoming CO_2 emission legislations may force car makers to develop vehicle powertrains distinguished by a high electrification level to avoid incurring into considerable regulatory sanctions.

TTW regulatory scenarios are discussed first (i.e. 2020TTW and 2030TTW). When optimizing for retail price and CO2 fine only, a PHEV embedding a 69kW ICE and a 4.0kWh battery pack is identified as the best option for both these scenarios in Table 8. When including the operative cost for a 60-month time span as well, an 81kW ICE may then be preferred to the 69kW one. As reported in Table 9, even though the 81kW ICE sizing option exhibits a higher retail price than the 69kW ICE option by around 300€, the related monthly operative cost is lowered by around 10€ which involves net savings of around 300€ over the considered vehicle lifetime. When moving to a vehicle lifetime of 120 months, all the powertrain sizing variables exhibit the same values compared with the 60 months TCO target for both TTW regulatory scenarios, yet the embedded battery pack capacity considerably increase to 9.8kWh. Compared to the 60-month TCO optimal option, the 120-month TCO optimal option exhibits a retail price increase by 2,700€, yet the reduced monthly overall operative cost of 28€ involves further net savings of around 3,600€ over the considered vehicle lifetime. The fuel consumption in WLTP associated to the optimal sizing options for all the considered optimization targets is 0

Table 8

Optimal P2 HEV powertrain sizing options for the considered OEM electrified fleet over different optimization targets and regulatory scenarios

Regulatory scenario code	Optimization target	$P_{ICE_{MAX}}$ [kW]	$P_{MG_{MAX}}$ [kW]	Battery capacity [kWh]	MG to gearbox ratio	$\tau_{G,tot}$	FD ratio
2020TTW	Retail price + CO_2 fine	69	29	4.0	2.25	4.00	3.40
	TCO (60 months)	81	29	4.0	2.25	4.00	2.60
	TCO (120 months)	81	29	9.8	2.25	4.00	2.60
2020WTW	Retail price + CO_2 fine	69	29	7.5	2.25	4.67	3.40
	TCO (60 months)	69	29	9.8	2.25	4.00	3.40
	TCO (120 months)	69	29	9.8	2.25	4.00	3.40
2030CETTW	Retail price + CO_2 fine	69	29	4.0	2.25	4.00	3.40
	TCO (60 months)	81	29	4.0	2.25	4.00	2.60
	TCO (120 months)	81	29	9.8	2.25	4.00	2.60
2030CEWTW	Retail price + CO_2 fine	69	29	7.5	2.25	4.00	3.40
	TCO (60 months)	69	29	9.8	2.25	4.00	3.40
	TCO (120 months)	69	29	9.8	2.25	4.00	3.40
2030FEWTW	Retail price + CO_2 fine	58	29	7.5	2.25	4.67	4.20
	TCO (60 months)	69	29	9.8	2.25	4.00	3.40
	TCO (120 months)	69	29	9.8	2.25	4.00	3.40
2030CESR	Retail price + CO_2 fine	69	29	9.8	4.00	4.67	3.40
	TCO (60 months)	69	29	9.8	2.25	4.00	3.40
	TCO (120 months)	69	29	9.8	2.25	4.00	3.40
2030FESR	Retail price + CO_2 fine	69	29	7.5	2.25	4.00	3.40
	TCO (60 months)	69	29	9.8	2.25	4.00	3.40
	TCO (120 months)	69	29	9.8	2.25	4.00	3.40

as the corresponding HEVs can complete a single WLTP cycle in pure electric operation.

Moving to the WTW regulatory scenarios that consider 2020 and 2030 regulatory emission limits currently set and current electricity production mix (i.e. 2020WTW and 2030CEWTW), the related optimal sizing options over different optimization targets exhibit the same trend in terms of ICE size, MG size and battery pack capacity. Particularly, a 69kW ICE and a 29kW MG are embedded in all the optimal sizing options over the considered optimization targets. Compared to the TTW regulatory scenarios, when optimizing for retail price and CO_2 fine only, the battery pack capacity is increased to 7.5kWh entailing a 1,400€ increase in the retail price. As shown in Fig. 10, the upsized battery pack allows lowering the regulatory CO_2 emission below 81g/km, i.e. the 2030 limit currently set by legislations. Similarly to the TTW regulatory scenarios, the battery pack capacity of the optimal sizing option is then increased to 9.8kWh when considering operative cost as well, yet the ICE size is maintained at 69kW in the considered WTW scenarios.

Considering WTW emissions as given by a cleaner electric production mix and the 2030 limit currently set (i.e. 2030FEWTW scenario), the identified optimal sizing candidates over the retained optimization targets do not exhibit substantial changes compared with the WTW regulatory scenarios considered above. This relates to the optimal HEV sizing candidates identified above already complying with the regulatory emission limits, even with a higher weight on the CO_2 term emitted by the electricity coming from the grid. Compared with the WTW regulatory

Table 9

Cost terms and energy performance of the optimal P2 HEV powertrain sizing options for the considered OEM electrified fleet over different optimization targets and regulatory scenarios

Regulatory scenario code	Optimiza-tion target	RP [k€]	CO_2 fine [€]	Month-ly fuel cost [€]	Monthly electricity cost [€]	EFC_{WLTP} [L/ 100km]	EE_{WLYP} [kWh/ 100km]	EFC_{RW} [L /100km]	EE_{RW} [kWh/ 100km]	J_{OEM} [billions of €]
2020TTW	Retail price + CO_2 fine	15.9	0	57	11	0.0	10.6	3.7	12.4	7.7
	TCO (60 months)	16.2	0	50	8	0.0	9.8	3.2	8.8	9.5
	TCO (120 months)	18.6	0	22	6	0.0	7.4	1.4	6.8	10.7
2020WTW	Retail price + CO_2 fine	17.3	0	44	11	1.5	7.6	2.8	12.1	8.4
	TCO (60 months)	18.3	0	23	6	0.8	7.6	1.5	6.9	9.7
	TCO (120 months)	18.3	0	23	6	0.8	7.6	1.5	6.9	10.5
2030CETTW	Retail price + CO_2 fine	15.9	0	57	11	0.0	10.6	3.7	12.4	7.7
	TCO (60 months)	16.2	0	50	8	0.0	9.8	3.2	8.8	9.5
	TCO (120 months)	18.6	0	22	6	0.0	7.4	1.4	6.8	10.7
2030CEWTW	Retail price + CO_2 fine	17.3	0	42	11	1.5	7.6	2.7	11.4	8.4
	TCO (60 months)	18.3	0	23	6	0.8	7.6	1.5	6.9	9.7
	TCO (120 months)	18.3	0	23	6	0.8	7.6	1.5	6.9	10.5
2030FEWTW	Retail price + CO_2 fine	17.0	0	43	11	1.9	11.2	2.8	11.9	8.2
	TCO (60 months)	18.3	0	23	6	0.8	7.6	1.5	6.9	9.7
	TCO (120 months)	18.3	0	23	6	0.8	7.6	1.5	6.9	10.5
2030CESR	Retail price + CO_2 fine	18.3	143	30	6	1.0	6.5	2.0	6.5	8.9
	TCO (60 months)	18.3	218	23	6	0.8	7.6	1.5	6.9	9.8
	TCO (120 months)	18.3	218	23	6	0.8	7.6	1.5	6.9	10.7
2030FESR	Retail price + CO_2 fine	17.3	89	42	11	1.5	7.6	2.7	11.4	8.4
	TCO (60 months)	18.3	0	23	6	0.8	7.6	1.5	6.9	9.7
	TCO (120 months)	18.3	0	23	6	0.8	7.6	1.5	6.9	10.5

scenarios considered above, only the ICE is further

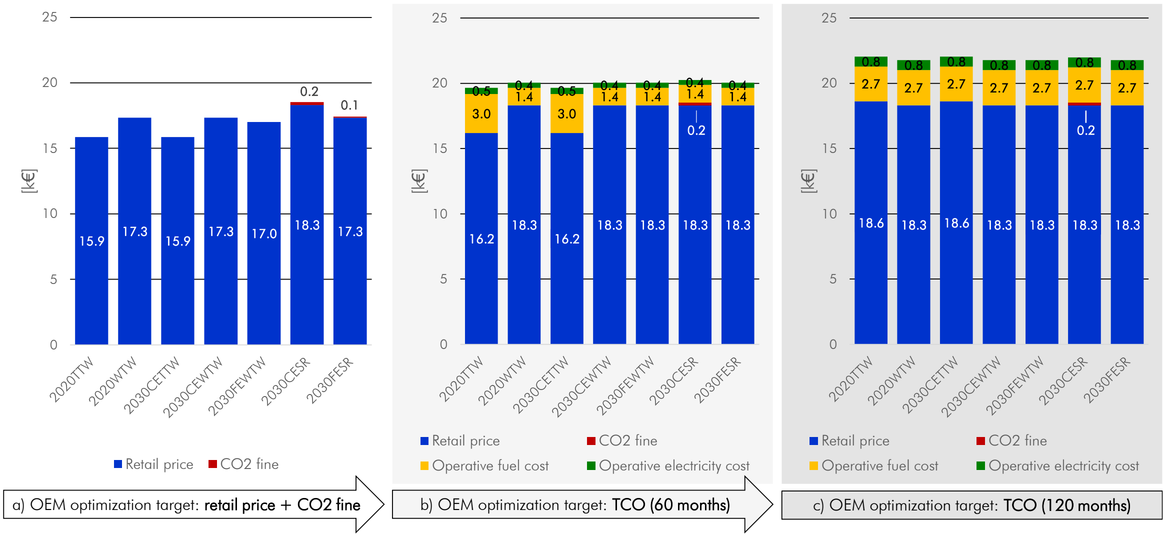


Fig. 11. Breakdown of the average vehicle cost terms for the optimal P2 HEV powertrain sizing options for the considered OEM electrified fleet over different optimization targets and regulatory scenarios.

downsized to 59kW when optimizing for retail price and CO_2 fine.

When it comes to scenarios involving a tightening in the CO_2 emission regulations, the identified optimal sizing options considering the current electricity production mix (i.e. 2030CESR scenario) never comply with the legislative limit of 59g/km. The sizing algorithm implemented in EFETool thus prefers adding a CO_2 fine ranging from around 140€/vehicle to around 210€/vehicle across the considered optimization targets than further increasing the battery pack capacity, since a higher retail price would overcome the potential reduction in the WTW CO_2 emission. As concerns optimal values of sizing variables, all the optimal options identified over the three optimization targets for the 2030CESR scenario embed the same ICE size (i.e. 69kW), the same MG size (i.e. 29kW) and the same battery pack capacity (i.e. 9.8kWh).

Stringent emission limits could be fulfilled through a cleaner electricity production mix as in 2030FESR scenario, where a CO_2 fine of around 90€/vehicle can be observed only for optimal sizing option related to the optimization target that considers retail price and CO_2 fine. In this case, the battery pack capacity for the identified optimal HEV option is downsized to 7.5kWh. On the other hand, following the trend of the remaining regulatory scenarios considered, a 9.8kWh battery pack is embedded in the optimal sizing options identified after including operative costs in the optimization target. Fig. 10 highlights how remarkably lower WTW CO_2 emissions can be achieved in this regulatory scenario that amount to around 40g/km.

The breakdown of the average vehicle cost terms illustrated in Fig.11(a) and the related values of J_{OEM} reported in Table 9 suggest that the considered regulatory scenario can have a high impact on the identified optimal HEV sizing option and the related value of objective function. On the other hand, looking at Fig.11 (b) and Fig.11 (c), similar values of objective function are achieved when including operative costs as well in the powertrain optimization process for the electrified fleet. Moreover, more uniform values of sizing parameters for the 120-month TCO optimization target can be observed across the considered regulatory scenarios compared with the optimization target that includes retail price and CO_2 fine only (e.g. recurrent embedment of a 69kW ICE, a 29kW MG and a 9.8kWh battery pack). This suggests that the optimality of the HEV sizing option identified by the car maker for the electrified fleet considering a 120-month TCO as optimization target is more robust with respect to the uncertainty of future regulatory scenarios compared with an HEV sizing methodology that considers vehicle retail price and CO_2 fine only in the vehicle development process.

7. Summary

This paper has discussed a CAE methodology that allows optimally sizing electrified powertrains for vehicle fleets of car makers including different vehicle models. The developed approach, named electrified fleet engineering tool (EFETool), integrates multiple evaluation metrics for the OEM fleet such as overall retail price, eventual regulatory sanctions for not complying with CO2 emission regulations, and real-world operative costs including fuel and electricity coming from the grid. Moreover, other than conventional vehicle design options, the full spectrum of electrification levels is considered including mild HEVs, full HEVs and PHEVs.

7.1. Performed case study

A case study is carried out considering the sizing process of a parallel P2 electrified powertrain for the interpolation family of an OEM fleet comprising four different vehicle models. Sizing parameters include the ICE size, the MG size, the battery pack capacity, and three transmission ratios including the total transmission ratio, the MG to gearbox ratio and the FD ratio. Different current and future legislative scenarios have been simulated considering both TTW emission and WTW emission scenarios with different weights on the CO2 emission contribution provided by the electricity coming from the grid and sweeping different values for the CO2 legislative limit. Furthermore, different optimization targets have been retained for sizing the electrified powertrain to be embedded in the OEM vehicle fleet including retail price and CO2 regulatory fine only, TCO over a time span of 60 months and TCO over a time span of 120 months.

7.2. Main findings

In general, for the illustrated test case, EFETool has identified a PHEV architecture as the optimal electrified powertrain layout for all the retained optimization targets and all the considered regulatory scenarios. This suggests that, form the perspective of a car maker, investing in research and development and in upgrade of current vehicle production facilities to develop highly electrified vehicles may represent a more strategic and successful approach than a conservative strategy which would restrain the economic investments and limit the overall electrification level of all vehicle models. The considerably higher retail price that the user is required to pay when purchasing a PHEV can in fact be paid off and eventually reveal beneficial in a long term given the avoidance of paying a regulatory CO2 sanction and the consistent reduction in the monthly operative cost in terms of fuel and electricity, as corroborated by other analyses performed in the literature [60][61].

As concerns the different optimization targets retained, obtained results also suggest that the optimal electrified powertrain sizing candidate identified for the retained OEM vehicle fleet may considerably vary according to the regulatory scenario if only retail price and CO2 fine are considered in the optimization process. On the other hand, if the actual use of the vehicle as operated by the final user is considered within the vehicle development process, the robustness of the identified electrified powertrain sizing solution considerably increases since limited sensitivity is exhibited related to the specific regulatory scenario. In this framework, the identified 60-month TCO optimal powertrain sizing solution exhibits comparable characteristics with the optimal sizing option identified by considering retail price and CO2 fine only and assuming a tightening in future CO2 emission regulations. This further suggests that future stringent regulations may potentially imply lowering fuel consumption and CO2 emissions not only in regulatory procedures, but also in real-world driving conditions.

7.3. Possible future work

Regarding related future work, the vehicle TCO model could be refined for example by including maintenance cost and financial incentives. Moreover, cost models of power components could be diversified as function of specific technologies. Different electrified powertrain architectures and vehicles sizes could be considered in the analysis. Finally, each vehicle of the OEM electrified fleet could be associated with a typical driving scenario corresponding to its specific operation, thus improving the accuracy of the developed EFETool.

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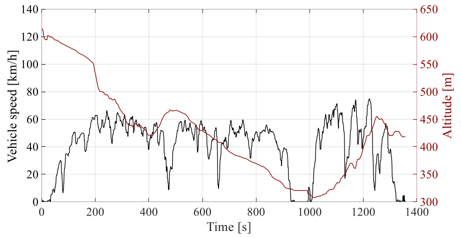
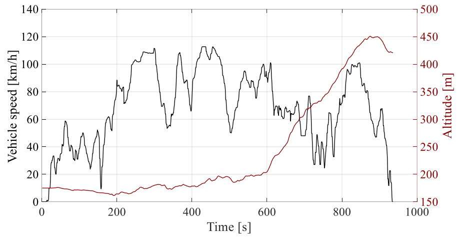
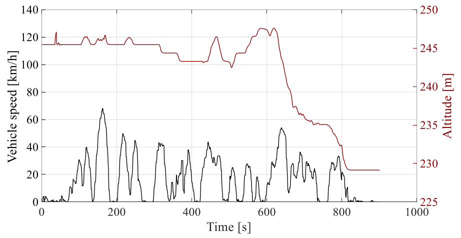
Appendix



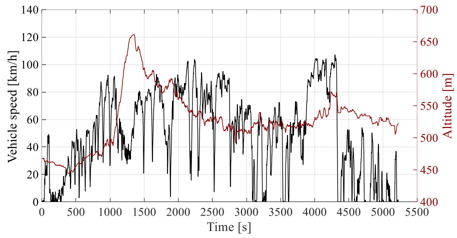
(a) "RWC01 – Downhill": vehicle speed and altitude



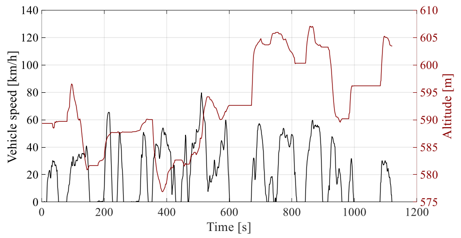
(b) "RWC02 – Uphill": vehicle speed and altitude



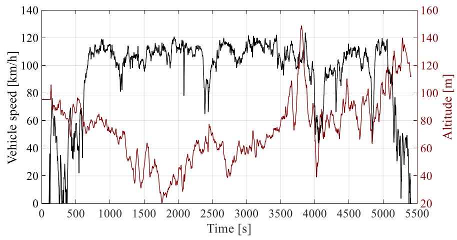
(c) "RWC03 – Urban01": vehicle speed and altitude



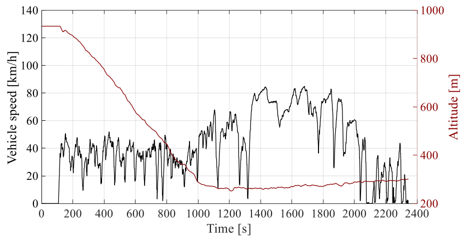
(d) "RWC04 – LongExtraUrban": vehicle speed and altitude



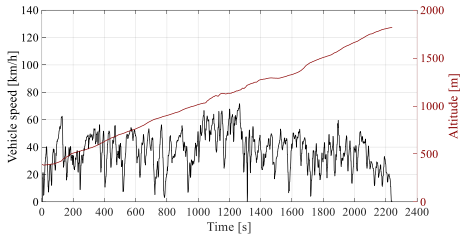
(e) "RWC05 – Urban02": vehicle speed and altitude



(f) "RWC06 – LongHW01": vehicle speed and altitude



(g) "RWC07 – Downmountain": vehicle speed and altitude



(h) "RWC08 – Upmountain": vehicle speed and altitude

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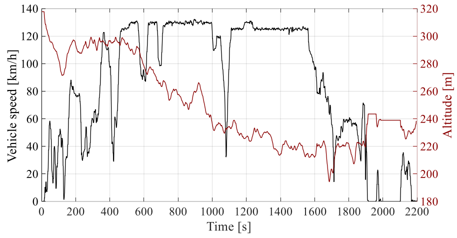

(i) “RWC09 – LongHW02”: vehicle speed and altitude

Figure 12. Vehicle speed profiles and road altitude profiles for the real-world driving missions recorded through global positioning system

Table 10

Statistics for real-world driving missions recorded through global positioning system

	D [km]	T [s]	v_{max} [km/h]	v_{avg} [km/h]	a_{avg+} [m/s^2]	a_{avg-} [m/s^2]	θ_{avg+} [%]	θ_{avg-} [%]	Δh_{max} [m]	Δh_{0-end} [m]
RWC01 - Downhill	15.6	1357	74.7	41.4	0.4	-0.5	7.6	-4.8	306.1	-195.4
RWC02 – Uphill	17.9	936	112.7	68.7	0.6	-0.6	3.6	-1.6	289.3	246.1
RWC03 – Urban01	4.1	901	68.0	16.5	0.6	-0.6	2.2	-3.0	18.4	-16.3
RWC04 – LongExtraUrban	71.9	5226	107.1	49.5	0.7	-0.5	3.9	-5.3	216.7	54.5
RWC05 – Urban02	6.3	1121	79.7	20.3	0.0	-0.7	5.9	-2.4	30.2	14.1
RWC06 – LongHW01	140.1	5417	123.6	93.1	0.3	-0.3	2.1	-1.9	128.4	16.9
RWC07 – Downmountain	27.4	2345	84.9	42.1	0.5	-0.5	3.5	-6.4	682.1	-633.0
RWC08 – Upmountain	23.2	2241	71.7	37.3	0.5	-0.7	7.5	-3.9	1434.5	1427.9
RWC09 – LongHW02	51.5	2197	132.3	84.3	0.4	-0.4	2.7	-2.3	123.5	-79.5

*** D = distance ; T = time ; v_{max} = maximum speed ; v_{avg} = average speed ; a_{avg+} = average acceleration ; a_{avg-} = average deceleration ; θ_{avg+} = average positive slope ; θ_{avg-} = average negative slope ; Δh_{max} = maximum altitude difference ; Δh_{0-end} = altitude difference between end and start.**